Journal of Information Assurance and Security.
ISSN 1554-1010 Volume 15 (2020) pp. 094-106

A contemporary Survey on Human Gait Recognition

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Abstract: **Global security related problems have increased to an extreme in recent days. Biometrics techniques are used to identify the individual by using physiological or behavioral characteristics. Based on the human walking style, gait recognition is the most emergent behavioral biometric trait. This has unique biometric features to identify people at some limited distance with minimal co-operation as compared with other biometric techniques such as voice, hand, face, iris, and fingerprint. Although there are a number of covariates such as viewing direction, type of cloth, type of shoe, walking surface, walking speed, carrying objects, etc., that affects the correct classification rate of gait recognition. It is necessary to evaluate and understand covariates in order to develop a dominant and reliable gait recognition system. The basic gait recognition system consists of acquisition of gait data, background subtraction, feature extraction, feature selection, and classification. This review paper proposes a broad understanding of the techniques used for gait recognition in order to achieve more accuracy for various gait databases.**

Keywords: Biometric, gait recognition, background subtraction, feature extraction, feature selection, classification, covariates, correct classification rate.

I. Introduction

Generally, people are walking in different styles. Each individual has a distinctive walking style. The way of representing the walking style of an individual is known as a gait. Time taken for one heel strike to the next heel strike of the same limb is termed as a gait cycle [1],[7]. The gait cycle provides complete information about the gait pattern. If the full gait cycle is not considered, the accuracy of the gait recognition is not achieved and hence the complete information on the gait cycle is necessary to increase the accuracy of a gate recognition system. A complete gait cycle pattern is shown in Figure1.

Gait cycle contains two important stages:

1. Stance phase (weight on the foot)
2. Swing phase (No weight on the foot)

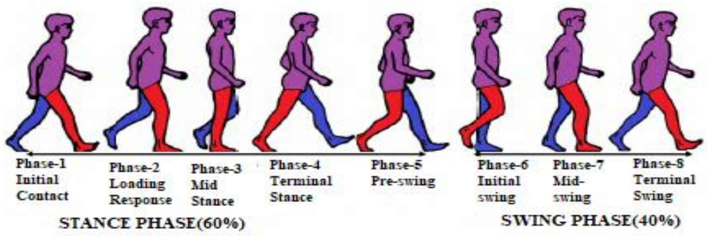

Figure 1. A complete gait cycle representation [1]

The phase during the gait period, when the heel of one leg touches or hits the ground and ends when the toe of the same leg lifts off is called the stance phase. In this phase, the entire time foot in touch with the ground. The stance phase constitutes 60% (approximately) of the gait cycle. Different stages of a stance phase throughout a gait cycle are:

i) Heel contact (~0-2%)
ii) Foot flat (~10%)
iii) Mid-stance (~30%)
iv) Heel off (~60%)

In a gait cycle, the toe-off on one foot and heel contact on the same foot is called the Swing phase. In this stage, the foot doesn't touch the ground. It constitutes 40% (approximately) of the gait cycle. Different stages of a swing phase during a gait cycle are:

i) Acceleration (60-73%)
ii) Mid-swing (87%)
iii) Deceleration (100%)

Various studies have shown that gait recognition is a powerful behavioral biometric technique for real-time surveillance and access control applications. Gait recognition method has numerous advantages as compared with the other widespread biometric techniques such as the face, iris, fingerprint, hand geometry, and speech recognition [2]-[5]. Few of the advantages of gait recognition systems are:

1. Gait is caught far away (10 m or more distance) from the subject.
2. It can be accomplished even with low-resolution video footage.
3. It can be done without the subject cooperation.
4. Features of gait are hard to be imitated.
5. It still works fine, even when the face is hidden from camera.
6. Gait recognition process can be accomplished the use of with simple equipments.

Owing to the above mentioned advantages, gait recognition is considered to be an appropriate biometric technique for real-time video-based applications. Gait recognition is considered to be one of the most useful and important research topics in computer visualization and pattern recognition. Many investigators proposed different solutions to improve gait recognition accuracy in the presence of various covariates. Covariates may be classified into different categories such as view direction variations, appearance variations (clothing differences, walking surface, shoe variety, carrying objects), and occlusion (due to many peoples walking in a crowd) [6]. Hence understanding these covariates is an essential task for researchers to design robust and efficient gait recognition algorithms.

The paper is arranged as follows. Section II describes the fundamental steps of a gait recognition system. Section III describes the brief reviews of the gait recognition methods. Section IV describes the gait datasets. Section V describes the performance evaluation metrics in gait recognition. Section VI describes the application of gait recognition. Finally, different challenges of gait recognition and conclusions are covered in Section VII and VIII respectively.

II. Fundamental steps of a framework for gait recognition

The fundamental gait recognition system is shown in Figure 2. That consists basically:

- Acquisition of gait data
- Silhouette extraction
- Feature extraction
- Feature selection
- Classification

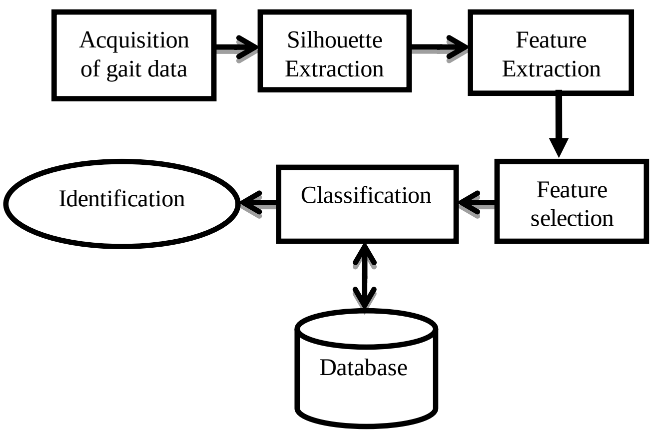

Figure 2. A Fundamental gait recognition system

A. Gait data acquisition

The collection of gait data is a crucial step in gait identification. The accuracy rate of the gait recognition depends mainly on the quality of input data collection. Different sources of data acquisition for the gait are listed below [8]:

i) Wearable sensors
ii) Floor sensors
iii) Radar
iv) Kinetic device
v) Camera, etc.

B. Silhouette extraction

In gait recognition, the silhouette extraction process is performed by using any one of the background subtraction techniques like Gaussian mixture method (GMM) [9], Frame difference, Least median of squares (LMedS) [10], etc. The primary emphasis of silhouette extraction is to decompose the human body structure into different parts. The extraction process of the silhouette is shown in Figure 3.

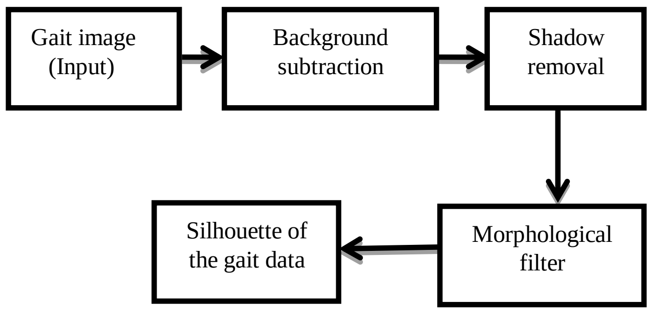

Figure 3. Silhouette extraction process.

The removal of shadow is an important criterion in silhouette extraction process. A proper threshold value (T) is used to eliminate the shadow from difference images. If the value of the threshold is not chosen correctly, then the segmentation is either under segmented or over segmented. In order to overcome this problem, different kinds of adaptive threshold techniques are proposed [81], [86]. Most of the researcher used morphological filters to eliminate noise that produced during the segmentation process.

C. Feature extraction process

The extraction of features is considered to be the most important part of any gait recognition system. There are several properties of gait that can be considered as a gait recognition feature. Later, the extracted features can be used to compare the similarities between the gait images. Therefore, the selection of the most appropriate features is of the utmost importance in order to accomplish high accuracy.

In the gait recognition process, either static or dynamic features are extracted (sometimes both the features are extracted). The static features are stride, body-height, and build. While Dynamic features are joint angle trajectories of the main limbs [11]. Direct extraction of features from segmented video sequences is a tedious task for classification.

The most widely used feature extraction techniques are:

- Principal Component Analysis (PCA) [12],[15]
- Local Directional Pattern (LDP) [13]
- Kernel Principal Component Analysis (KPCA) [14]
- Linear Discriminant Analysis (LDA) [15]
- Local Binary Pattern (LBP) [15]
- Independent Component Analysis (ICA) [12], etc.

Table1 represents a similarity comparison between different feature extraction techniques and gait features.

Technique	Spatio-temporal data	Linear Structure	Non-Linear Structure	Local Feature	Global Feature
PCA	✓	✓			✓
KPCA	✓		✓		✓
LDA	✓	✓		✓	✓
ICA	✓		✓	✓	
LBP	✓		✓	✓	
LDP	✓		✓	✓	

Table 1. Different feature extraction techniques and their similarities.

D. Feature selection process

Once a feature extraction process is completed, the selection of optimized features is another important step in gait recognition. In this stage, a suitable subset of features is selected to achieve maximum accuracy by removing the redundant and inappropriate gait features.

The most extensively used feature selection techniques in gait recognition are [16]:

- Principal Component Analysis (PCA)
- Support Vector Machine (SVM)
- Particle Swarm Optimization (PSO)
- Discrete Cosine Transform (DCT)
- Genetic Algorithm (GA), etc.

E. Classification

In classification process, the input video frames are compared to the sequences stored in the database. Different classifiers ranging from a traditional nearest neighbor (*k*-NN) to the latest Deep Neural Networks (DNN) are available to classify the data for gait recognition.

For gait feature classification, the most commonly used classifiers are:

- Hidden Markov Model (HMM) [18]
- Support Vector Machine (SVM) [17]
- Navie Bayes [19]
- Deep Conventional Neural Networks [20]
- K-nearest neighbor (K-NN) [21]

Table 2 represents the advantages and disadvantages of most frequently used different classifiers.

Classification Technique	Advantages	Disadvantages
k-NN classifier	i) Easy to implement. ii) Robust to noise iii)Instance-based learning	i) It does not work well with large data set. ii) Does not work well with high dimensions iii) Feature scaling is required
Deep Conventional Neural Networks (DCNN) classifier	High accuracy	i) It requires a good GPU for training ii) It needs more training data iii)High computational cost
Navie Bayes classifier	i) Very simple to implement ii) It requires less training data iii) It makes probabilistic predictions	Unable to make the predictions
Support vector machine (SVM) classifier	High accuracy	Not suitable for large datasets.

Table 2. Summary of some important classifier's advantages and disadvantages for gait recognition.

III. Gait recognition Methods

Generally, two of the most extensive methods are used to signify and extract the features of gait are:

- Model-based method [22-24]
- Model-free method [25],[26]

In the model-based approach, the structure of the human body is considered and features such as i) Trajectory-based kinematic features ii) Static features (stride length, limb lengths, cadence, stride speed, etc.), and iii) dynamic features (joint trajectories) are extracted. Such features are very insensitive to background noise, and this approach requires high-resolution video to extract the features. The design of this approach has high computational complexity and it is both viewable and scale-invariant.

In the model-free method, the human body structure is not considered directly but the motion or shape of the gait silhouettes is considered as a feature. In comparison to the model based approach, this approach has less computational cost. The model-free approach is also called a holistic approach or an appearance-based approach.

The Table 3 represents the basic possibilities of gait recognition approaches in terms of complexity, calculation, and covariates.

Parameters/Approach	Model-free method	Model-based method
Complexity	✓	✗
Calculation	✗	✓
Covariates	✓	✗

Table 3. Comparison of gait recognition approaches [85].

A. Model-based gait recognition method

In the model-based gait recognition method, the structure of the human body components (lower part.) is considered to be part of the gait recognition process. This approach performs the model fitting for the extraction of kinematic parameters such as lower joint angles, speeds, and segment positions. A model-based approach is robust to scale and vision. A model-based gait recognition process is illustrated in Figure 4.

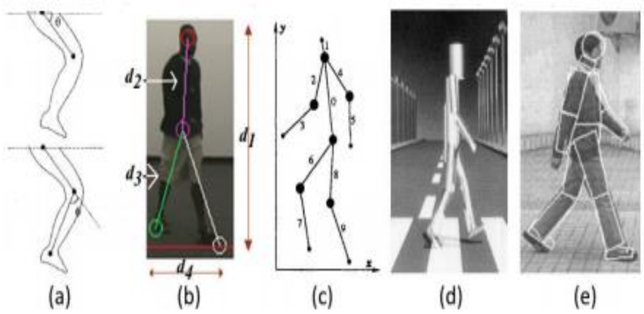

Figure 4. Illustration of Model-based feature extraction [83].

Summary of the mode-based approach of different techniques, features, and classifiers proposed by various researchers are tabulated in Table 4.

Year	Reference	Technique	Gait Features	Classifier
2001	Bobick *et al.*[27]	Parametric based approach	Static and stride based parameters	k-NN
2001	Rawesak *et al.*[28]	Trajectory-based gait motion estimation	Dynamic features	NN
2002	Abdelkader *et al.*[29]	Parametric approach	Height and stride parameters	-
2003	Yam *et al.* [30]	Forced coupled oscillator pendulum model	Thigh and leg motion features	k-NN, BPNN
2004	Wagg *et al.* [31]	Hierarchical silhouette	static parameters	NN+ ANOVA
2004	Urtasum *et al.*[32]	3-D based gait model	Temporal motion-based parameters	k-Means algorithm
2006	Zaho *et al.*[33]	3-D gait model	Static features	LTN for matching and recognition
2007	Bouchrika *et al.*[34]	-	Static and Dynamic gait features	-
2008	Yoo *et al.*[35]	2-Dimensional stick Figure	Trajectory-based kinematic features	BPNN
2009	Kim *et al.*[36]	Silhouette template matching	Active shape features	Prediction based-hierarchical ASM
2010	Tafazzoli *et al.*[24]	Active contour Model	Kinematic features	-
2010	Gu *et.al.* [37]	3-Dimensional Gait approach	Complete body Lower limb features	MAP
2010	Zhang *et al.*[38]	Dual gate generative model	Kinematic gait features	-
2010	Goffredo *et al.*[39]	Trajectory-based gait motion estimation	Dynamic features	k-NN
2011	Yoo *et al.* [40]	2-Dimensional stick figure	Motion-based parameters	k-Nearest Neighbor
2013	Zeng *et al.* [41]	Deterministic learning	Lower limb joint angles of Silhouette	RBF NN

2014	Bouchrika *et al.*[42]	Template matching using Harr method	Kinematic features of gait	k-Nearest Neighbour
2014	Kwolek *et al.*[43]	3-D gait model	Spatio-temporal feature descriptor	NB, MLP
2015	Bouchrika *et al.*[44]	Elliptical Fourier descriptor	Angular and spatial measurement of body	-
2015	Kastaniotis *et al.*[45]	Pose estimated gait representation model	Dynamic features	k-NN
2016	Wang *et al.* [46]	3-D gait model	Static and dynamic features	NN
2016	Fernandez *et al.*[47]	3-D voxel	3-D dynamic features	SVM , PCA , LDA
2016	Chen *et al.* [48]	Hyper graph partition approach	3-D tensor gait features	NN
2017	Chen *et al.* [49]	Trajectory-based gait motion estimation	Dynamic Feature Extraction	L-CRF , SVM
2017	Khan *et al.* [50]	Spatiotemporal motion characteristic	Stride length, gait patterns, and other shape templates.	SVM
2018	Kim *et al.* [51]	3-D gait model	hip/knee/ankle	k-NN
2018	Zhen *et al.* [52]	Deterministic learning and Microsoft Kinect sensor	Dynamic features	-
2018	Sokolova *et al.*[53]	Pose-based gait descriptors.	Silhouette based	CNN
2019	Ben *et al.* [54]	Coupled bilinear discriminant projection (CBDP)	GEI based features	-
2019	Sadeghzadehyazdi *et al.*[55]	Glidar 3DJ	2D skeleton model	k-NN
2019	Duan *et al.* [56]	WiMGNet	Energy distribution map (EDM)	WiID

Table 4. Summary of the model-based approach of different techniques, features, and classifiers used by researchers in their work.

B. Model-Free (or) Appearance-based gait recognition method

In the model-free method, the features are not directly extracted from the human structure, but they are extracted from the moving shape or motion of the subject silhouettes. The silhouettes extraction process is an appropriate technique for gait representation, but due to different covariates, the accuracy rate falls drastically, and therefore, in order to overcome this problem, various authors have recently proposed advanced techniques in this field. Few of them are as listed in Table 5.
A Model-free gait recognition process is illustrated in Figure 5.

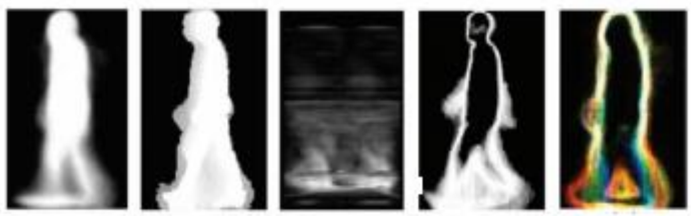

Figure 5. Illustration of Model-free feature extraction [83]

The model-free approach consists of two methods as listed below:

i) Spatio-temporal method.
ii) Statistical method.

Spatial parameters are also called as distance parameters. Step and stride are the two significant spatial parameters in gait recognition. Temporal parameters are time-related parameters. Cadence, speed of gait and single limb support, double limb support, etc. are the temporal parameters. In the gait recognition process, the silhouette of a gait is the most essential statistical parameter used to evaluate the shape and motion patterns of the gait. In the model-free gait recognition approach, the silhouette of gait offers greater recognition accuracy as compared with the kinematics in the model-based approach. These parameters are not affected by noise easily.

Traditionally, in a spatial-temporal approach, gait is defined as a sequence of patterns, consisting of more space and complication for analysis. To overcome this problem Bhanu *et al.* [57] suggested a new technique 'Gait Energy Image (GEI)' for gait representation. Gait Energy Image models are not easily affected by noise (less sensitive).

For a gait cycle, GEI mathematically characterized as

$$G(a,b) = \frac{1}{N}\sum_{n=1}^{N} I_n(a,b) \qquad (1)$$

where

N -Number of frames in silhouette
n - Frame number in the sequence.
$I_n(a,b)$ - Original silhouette of an image.
(a, b) - 2-D coordinates system values.

Figure 6 illustrates the representation of a human subject by GEI.

Figure 6. Representation of a subject by GEI [84]

Summary of the mode-free approach of different techniques, features, and classifiers proposed by various researchers in their research work for different gait databases is shown in Table 5.

Year	Reference	Technique	Gait Features	Classifier
2002	Wang *et al.* [58]	Statistical shape analysis	Procrustes shape analysis method to extract shape signature features	NN, k-NN, ENN
2002	Wang *et al.* [59]	Statistical principal component analysis	Eigen transformation for silhouette shape features	NN
2002	Abdelkader *et al.* [60]	Physical parameters (stride length and cadence)	Spatiotemporal features	Bayesian decision approach
2002	Collins *et al.* [61]	Physical parameters	Shape features and gait parameters	NN
2003	Sundaresan *et al.* [62]	Temporal based approach	HMM features	Distance matrices
2004	Wang *et al.* [63]	Model-based + appearance-based approach	Statistic features and dynamic features	ENN
2005	Boulgouris *et al.* [64]	Linear time normalized method	Silhouette features, angular features	Linear discriminant analysis
2006	Havsai *et al.* [65]	Spatiotemporal method	Symmetry features	Kernel Fisher discriminant analysis
2006	Shutler *et al.* [66]	Statistical features (based on shape and moments)	Zernike moments	k-NN
2009	Sarkar *et al.* [67]	Gait entropy image (GEnI)	Static and dynamic features	Adaptive component and discriminant analysis (ACDA)
2012	Wang *et al.* [68]	Chrono-Gait Image	Contour of silhouette images	NN, PCA, LDA
2014	Kusakunniran *et al.* [69]	Spatio-temporal domain	Space-time interest points (STIP)	NN
2015	Rida *et al.* [70]	Supervised feature extraction method	Discriminative human body features-E	Modified phase-only correlation
2016	Rida *et al.* [71]	GEI	Discriminative human body features	Canonical discriminant analysis, PCA and multiple discriminant analysis
2016	Nandy *et al.* [72]	Statistical GEI	Statistical features based on GEI edge contour features	k-NN, Navie Bayes, decision tree, random forest
2017	El-Alfy *et al.*	Geometric View	Silhouette features	

	[73]	Transformation Model		-
2017	Isaac *et al.* [74]	Genetic template segmentation (GTS)	GEI, GEnI and AEI templates	PCA
2017	Wang *et. al.* [75]	GEI and Gabor wavelets	2-D PCA	SVM
2018	Babaee *et al.* [76]	G.E.I	-	CNN
2018	Xu C. *et al.* [77]	G.E.I	FFD	Neural Networks (NN)
2019	Zhang Y *et al.* [78]	G.E.I	-	Joint CNN
2019	Tian *et al.* [79]	View Transformation Model (VTM)	GEI based	SVM
2019	Chi Xu *et al.* [80]	single-support GEI (SSGEI)	GEI based	Gabor filtering and spatial metric learning

Table 5. Summary of the mode-free approach of different techniques, features, and classifiers used by researchers in their work.

IV. Openly existing Gait datasets and Performance evaluation

There are few datasets are openly available for gait recognition such as USF Dataset, OU-ISIR Gait Dataset, The CMU Motion of Body (MoBo) Database, CASIA Gait Dataset, TUM-IITKGP Dataset, TUM GAID database, SOTON database and The AVA Multi-View Dataset (AVAMVG) for gait recognition [82]. Different gait databases with the number of subjects and different covariates are provided in Table 6. Compared to all databases, the CASIA Gait Dataset was most widely used to compare and evaluate the performance of the gait recognition algorithms by researchers.

Year	Database		Subjects	Covariates
2001	CASIA gait database	A	20	View angle
		B	124	View angle
		C	153	Gait Speed , Carrying conditions
2001	CMU moBo database		25	View angle, speed, carrying conditions, surface incline
2001	SOTON database	Small	12	View
		Large	115	
2012		Temporal	25	View, time
2002	Human ID challenge gait database		122	View, surface, shoe, carrying Conditions
2007-2012	OU-ISIR database	A	34	Speed
		B	68	Clothing
		D	185	Gait fluctuations
2012	TUM GAID database		305	Season based (winter and summer) with cloth variation

Table 6. Openly available various gait datasets.

The Table 7 and Table 8 summarize different types of model-based and model-free gait recognition approaches proposed by various authors with different gait databases, techniques, and classifiers and correct classification rate (CCR). The Correct classification rate is very sensitive to a small change in any parameter or method.

Reference	**Type of Database**	**Technique**	**Classifier**	**Accuracy (CCR %)**
Yoo *et al.* [35]	Southampton HID Database	2-D Stick Figure	BPNN	90%
Wagg *et al.* [31]	HID Database	Hierarchical	NN+ ANOVA	Indoor: 84% Outdoor: 64%
Bouchrika *et al.* [42]	CASIA-B	Harr Template Matching	*k*-NN	73.6%
Zaho *et al.* [33]	CMU Mobo Database	Static Features	LTN For Matching and Recognition	70%
Zeng *et al.* [41]	CASIA-A, CASIA-B	Deterministic Learning	RBF Neural Network	CASIA-A: 92.5% CASIA-B: 91.9%
Kastaniotis *et al.* [45]	Created 30 Subjects	Pose Estimated Gait	k-NN	93.2%

	Gait Data			
Goffredo *et al.* [39]	SOTON Database , CASIA Dataset B	Trajectory-Based Gait Motion Estimation	*k*-NN	SOTON: 95.8% CASIA- B: 73.6%
Chen *et al.* [48]	Created 120 Subjects Multi Gait Data Set	Hyper graph Partition Approach	NN	2-Partcipants:89.2% 3-Partcipants:88.3% 4-Partcipants:87.2%
Chen *et al.* [49]	CASIA-B	Trajectory-based gait motion estimation	L-CRF, SVM	67.82%
Khan *et al.* [50]	TUM GAID database, CASIA-B, CASIA-C	Spatiotemporal motion characteristic	SVM	TUM GAID: 96.5% CASIA-B: 95.6% CASIA-C: 99.8%
Kim *et al.* [51]	-	Kinect skeleton method	k-NN	More table and accurate
Zhen *et al.* [52]	multi-view Kinect-based gait (MKG) database	Deterministic learning and Microsoft Kinect sensor	Dynamic features	Vary with respect to probe and gallery set view angle
Ben *et al.* [54]	CASIA-B, OU-ISIR	Coupled bilinear discriminant projection (CBDP)	-	Vary with respect to probe and gallery set view angle
Sadeghzadehyazdi *et al.* [55]	-	Glidar3DJ	k-NN	85.11%
Duan *et al.* [56]	-	WiMGNet	WiID	98.8%

Table 7. Comparison of different model-based gait recognition approaches proposed by various authors for different gait databases with accuracy rate (CCR %).

Reference	Type of Database	Technique	Classifier	Accuracy (CCR %)
Havsai *et al.* [65]	Created 1000 samples	Spatio temporal method	Kernel Fisher discriminant analysis	97%
Kusakunniran *et al.* [69]	CASIA-B	Spatio temporal domain	NN	63.6%
Sarkar *et al.* [67]	CASIA dataset, SOTON Small dataset	Gait entropy image (GEnI)	Adaptive Component and Discriminant Analysis	CASIA : 55.5% SOTON : 54.5%
Nandy *et al.* [72]	OU-ISIR treadmill dataset	Statistical GEI	k-NN, Navie Bayes, decision tree, random forest.	83.3%
Wang *et al.* [68]	USF Human ID gait dataset, CASIA dataset, SOTON large dataset	Chrono gait image (CGI)	NN, PCA, LDA	Rank1: 61.69% Rank5: 79.12%
Rida *et al.* [71]	CASIA dataset B	GEI	Canonical discriminant analysis, PCA, multiple discriminant analysis	88.75%
Isaac *et al.* [74]	CASIA–B (90^0 view)	Genetic template segmentation (GTS)	PCA	95.5%
Chi Xu *et al.* [80]	OU-ISIR Treadmill Dataset A, CASIA-C	Single-support GEI (SSGEI)	Gabor filtering and spatial metric learning	≈100%

Table 8. Comparison of different model free gait recognition approaches proposed by various authors for different gait databases with accuracy rate (CCR %).

From the extensive literature review, it is found that, in order to achieve a high percentage of CCR the following points to be considered:

i) Create Accurate multi gait database
ii) Consider different view angles
iii) Choose best recognition approaches
iv) Apply robust techniques for feature extraction

v) Select optimized features
vi) Apply multiple classification techniques (classifiers).

V. Performance evaluation metrics in Gait Recognition

Gait recognition is performed based on two classes [1]:

- Intra-class: Intra-class objects are identical with small variations
- Inter-class: Inter-class objects are dissimilar with more variations

Based on the class of information gait recognition is performed in two stages:
i) Identification mode: In this mode of operation, the gait recognition system compares the signature of the gait to all known signatures of the gait. In this mode, the recognition of the gait performed with a 1: N ratio.

ii) Verification mode: In this mode of operation, the gait recognition system compares the identity to the existing data. In this mode gait recognition performed with a 1:1 ratio.

The gait recognition performance evaluation metrics is used for evaluating the ability of an algorithm to accurately identify the subject. Following are some key parameters used for evaluation:

i) Rank order
ii) Cumulative match characteristics (CMC)
iii) False non-match rate (FNMR)
iv) Equal Error Rate(ERR)
v) False match rate (FMR)

Some other useful metrics used to evaluate the performance of a gait recognition system are listed below, from equation (2) to (6).

Precision (P):

Positive predictive value

$$P = \frac{TP}{FP + TP} \tag{2}$$

Where TP: True Positive (No. of correct detections)

FP: False Positive (No. of false detections)

Recall (R):

Probability of detection value

$$R = \frac{TP}{FN + TP} \tag{3}$$

Where FN: False Negative (No.of positives missed incorrectly)

Specificity (SP):

$$SP = \frac{TN}{TN + TP} \tag{4}$$

Where TN: True Negative (No. of correct non-detections)

F-Score:

Test accuracy measure

$$F = \frac{2 * P * R}{P + R} \tag{5}$$

CCR (Correct Classification Rate):

$$CCR = \frac{\text{Number of correct classifications}}{\text{Total number of subjects}} * 100 \tag{6}$$

VI. Applications of Gait Recognition

Gait recognition is one of the significant behavioural biometrics used in video-based security-related applications such as forensics, terrorism, etc. to recognize suspects. Nowadays, gait recognition is the most demanding technique in pattern recognition and computer vision applications for gender classification (Male/Female), age estimation, and clinical applications for Parkinson's disease identification, knee-related problems for orthopedic physicians based on the gait pattern measurements (Cadence, step length, step motion speed, etc.) [1].

After a broad survey conducted for gait applications for gender classification and age estimation related applications, most of the authors used SVM (support vector machine), Probabilistic neural network (PNN), Hidden Markov Model (HMM) as a classifier to achieve a high classification rate. In clinical applications, principal component analysis (PCA), Gaussian neural networks (GNN) used to detect the disease with high accuracy.

VII. Challenges of Gait Recognition

Gait recognition has unique characteristics as compared with other biometric techniques. The main goal of any biometric technique is to identify the person with high accuracy, but gait recognition affected with different covariates such as carrying things, viewing angle disparities, type of walking surface, cloth types, footwear, elapsed time, occlusions, and physical problems (leg injuries) [1].

These challenges are mainly classified as:

- Internal factors (Lower limb disorder, Aging, Weight loss, Pregnancy, etc.)
- External factors (View angle, Clothing variations, carrying things, etc.)
- Type of Occlusion (Static /Dynamic)

Occlusion is the most common complication in the process of gait recognition. Occlusion mainly occurs when two or more peoples walking in a group when the subject can conceal the gait patterns. View angle and appearance changes are the two more severe challenging problems in Gait recognition. Generally, the subject may be at any angle (between 0^0 to 180^0) to the camera and the subject may wear different clothing, carry different items so that the feature extraction process becomes a difficult task to define the gait more precisely. The selection of optimal features of the gait, which are invariant for covariate conditions is an important task to improve the performance of a gait recognition system.

VIII. Conclusion

Gait recognition is considered to be one of the foremost behavioural biometrics owing to its unobtrusive and non-perceivable features that can be applied to visual tracking applications. This paper describes a broad analysis of contemporary issues in the field of human gait recognition. Most of the authors used the k-NN classifier as a primary method in the classification process. Recently, deep learning classification models have shown promising results in the process of gait recognition, although deep learning models need more data set to work. And this paper broadly discusses the feature extraction process used in the model-based and model-free methods, because the process of extraction of features plays an important role to obtain the correct classification rate. After the conduction of the state-of-the-art survey in human gait recognition, it is concluded that more effort is needed to achieve a high accuracy rate under various conditions. CASIA-B is the largest and most widely used gait database that includes various covariate factors.

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