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Vision-Based Gait Recognition: A Survey

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ABSTRACT In the digital world of today, global security issues have given rise to video surveillance devices. Gait-based human recognition is an emerging behavioral biometric trait for intelligent surveillance monitoring because of its non-contact and non-cooperation with subjects. Other benefits of gait recognition in video surveillance are that it can be acquired at a distance and help to identify an object under low-resolution videos. This paper surveys extensively the current progress made towards vision-based human gait recognition. This paper discusses historical research that performs analysis of gait locomotion and provides information on how gait recognition can be performed. This paper describes measuring metrics that can be used to measure the performance of gait recognition model under verification and identification mode. This paper also provides an up-to-date review of existing studies on gait recognition representations (model based and model free). We also provide an extensive survey of available gait databases used in state-of-art gait recognition models, created since 1998. Furthermore, it offers insight into open research problems that help researchers to explore unripe areas in gait analysis, such as occlusion, view variations, and appearance changes in gait recognition. This paper also identifies the future perspectives in gait recognition and also outlines the proposed work.

INDEX TERMS Biometric, gait analysis, gait recognition, gait representation, pattern recognition, feature extraction.

I. INTRODUCTION

In modern digital society, reliable authentication of individual person becomes a fundamental necessity in many real-time applications (such as forensics, international border crossing, financial transactions, and computer security). Human body characteristics (such as face, iris, voice, and gait) play a vital role in recognizing individual over the thousands of year. Such biological characteristics that can uniquely identify a human being are termed as biometric features. Thus, biometrics may be termed as a measurement of biological characteristics of humans to claim an identity. Biometric system is classified into different traits based on physiological and behavioral characteristics as shown in Fig. 2; each has own strength and weakness. Any human physiological and behavioral characteristics can be used as a biometric parameter for recognition if it satisfies the following properties [1] that are, uniqueness, permanence, universality, collectability, performance, acceptability, and circumvention. Fig.1 depicts the market share of different biometric modalities reviewed in the year 2017 [141] and found that face recognition system has covered 39% of the market. Jain *et al.* [1] has reviewed different biometric traits and has stated that face, signature,

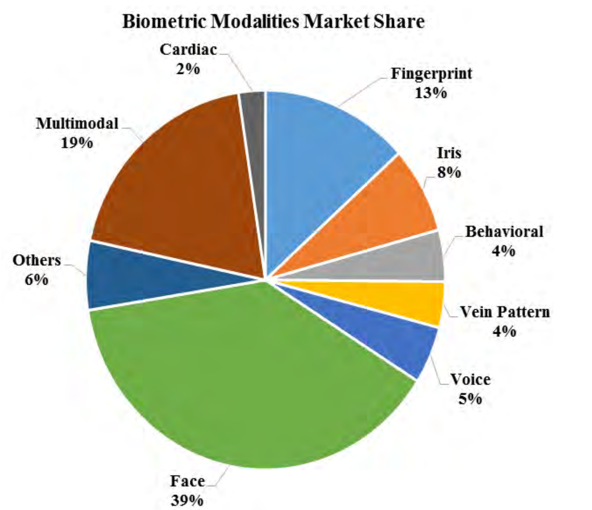

FIGURE 1. Outlines the market share of biometric modalities review the year 2017 [141].

and voice are very prone to circumvention as compared to DNA, ear, gait, iris, and odor. Among the different biometric traits, gait a behavioral biometric trait has drawn more

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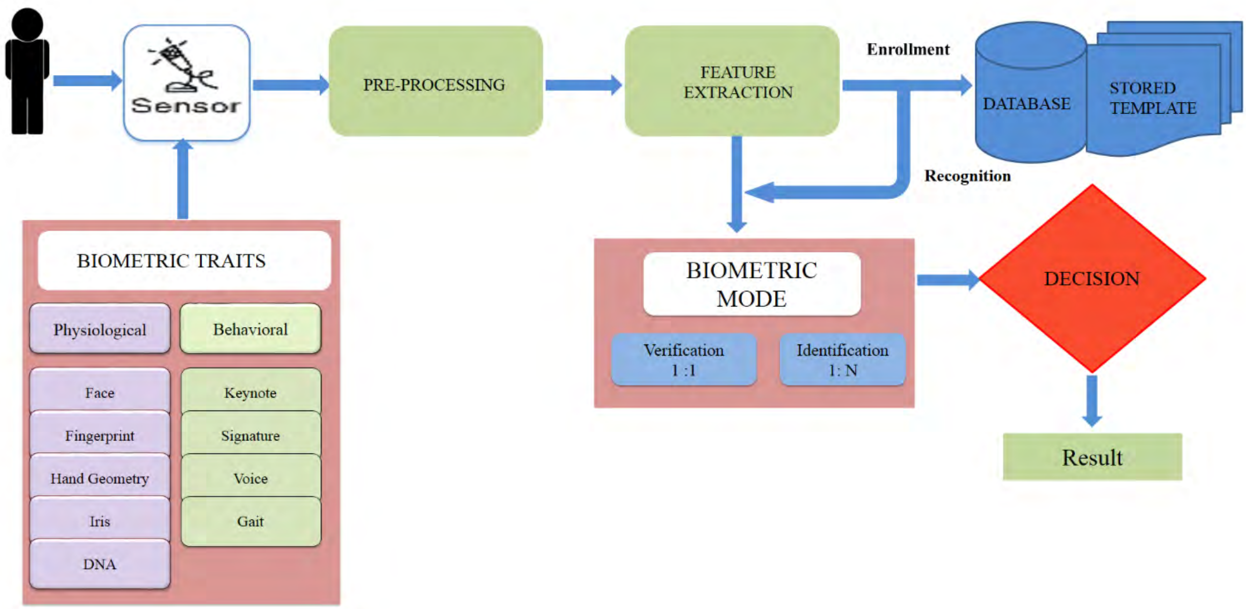

FIGURE 2. Generalized working of the biometric system with different biometrics traits and modes (verification and identification) [1] [38].

attention to computer vision researchers because of the following benefits [2], [33], [134]:

- Each person sufficiently has a distinctive uniqueness in walking style.
- Individual subject gait features without cooperation can be extracted from a distance of 10m or more.
- Gait characteristics can be analyzed from low-resolution video sequences.
- Unlike signature, it cannot be possible to conceal and disguise gait characteristics.

Because of this unobtrusive, noninvasive and non-perceivable nature, gait based recognition system is most beneficial in intelligent visual surveillance monitoring. The early studies of human gait in medical diagnosis and psychological analysis [3], [4], [19] reveal that human gait has 24 different components and if all these components are considered, human gait is unique for individuals. Human gait analysis in health care help to diagnose medical diseases that are related to gait such as Parkinson patient diagnosis, orthopedic patient diagnosis. In gait-related deficiencies, physiotherapist and orthopedic experts monitor and analyze gait movement patterns of these patients such as stride length, step length, stance and swing phase [5] to identify, whether improvement has taken place.

Recently, in the field of computer vision and motion analysis, the focus has been primarily on automatic human recognition based on individual movement patterns, which has led to the extensive research focus on video-based gait recognition. Johansson [6] and Cutting and Kozlowski [7] employed moving light display and reflectors on different body joints of human and made observations that gait patterns are unique and useful as a biometric feature of a human for recognition. The first gait recognition approach, based on spatiotemporal features of human walking contours, has been developed by Niyogi and Adelson [8]. They developed their approach for frontoparallel view consisting of 26 subject image sequences and achieved an accuracy of 81%. With a growing demand for automatic gait recognition, some of the famous universities and research institute have conducted much research and proposed approaches on gait recognition. Among these, Osaka University (OU-ISIR) has built the largest gait database [40], which is publically available under license agreement.

Aforementioned advantages prove that human authentication based on gait signature is an important research area in computer vision and pattern recognition. However, researchers face several issues that make gait recognition a complicated task due to following reasons: (1) view angle variations [30], [117], [135], (2) appearance changes due to clothing variations, carrying conditions, walking surface, shoe type [95], [96], [134], (3) occlusion due to multiple people walking in a group [61], [90], [110]. These issues in gait recognition have open new thrust areas for researchers.

There are existing surveys by different researchers that provided their reviews on gait recognition. A recent review by Patrick and Ross [9] focused on sensing modalities (such as vision, underfoot pressure and accelerometer) that are used for capturing gait motion parameters. They had also covered different feature extraction methods based on these modalities. Detailed information for important survey papers as on July 2018 are summarized in table 1 with their references and referred Google Scholar for a number of citations.

In this article, we surveyed the current state-of-the-art literature and selected articles that mostly discussed vision-based feature extraction techniques for model-based and model-free

TABLE 1. Summarized year wise survey papers on gait recognition with their citation details till July 2018.

Authors/year	Title	Journal/Conference	Work Discussed	No. of Ref.	No. of Citations
Patrick et al. [9] / 2018	Biometric recognition by gait: A survey of modalities and features	Computer Vision and Image Understanding	Discussed sensing modes (vision, under foot pressure and accelerometers) and features extracted based on these modes for gait recognition.	209	3
Sprager et al. [21]/2015	Inertial Sensor-Based Gait Recognition: A Review	Sensors	They surveyed gait recognition based on inertial sensors (accelerometers, gyroscopes).	86	77
Lv et al. [24] /2015	Class Energy Image Analysis for Video Sensor-Based Gait Recogntion: A Review	Sensors	They focused existing class energy images that played an important role in representation of appearance based gait recognition.	96	20
Lee et al. [2]/2014	A comprehensive review of past and present vision-based techniques for gait recognition	Multimedia Tools and Applications	They discussed vision based approaches for gait recognition and outlined 17 gait datasets. They also represented the fusion of gait with face for recognition.	132	45
Shirke et al. [136]/ 2014	Literature Review: Model Free Human Gait Recognition	Fourth IEEE conference on communication systems and network technologies	They surveyed model-free gait recognition approaches. Focused on feature extraction for model-free gait representation.	26	13
Weijun et al. [140] / 2012	Gait analysis using wearable sensors	Sensors	The focus of this article is on wearable sensors that can be used for gait analysis. They also outlined the application of gait based on wearable sensors.	182	441
Wang et al. [137] /2010	A Review of Vision-based Gait Recognition Methods for Human Identification	IEEE conference on digital Image computing: Techniques and Applications	They surveyed both model based and model-free gait representation approaches .They discussed three issues in gait recognition i.e image representation, data reduction and classification.	60	160

gait representation as well as classification techniques and covering covariate conditions. The objective of this survey article is to expand on previous surveys.

1) The paper comprehensively described the architecture of gait recognition and gives a short description of gait recognition evaluation parameters.
2) The article extensively reviewed feature extraction approaches in model-based and model-free gait representation and also outlined issues with these methods and provided solutions.
3) Investigate thirty-three gait dataset available for research in gait recognition based on taxonomy shown in Fig. 10.
4) The article investigates open research challenges of gait recognition in real time environment namely, view variations, occlusion, and appearance changes.
5) Including more than seventy gait publications of reputed journals and conferences based on vision-based that is not discussed in the previous surveys.
6) We provide a short discussion on the application area of gait recognition (i.e., soft biometric and clinical analysis).
7) We also outline future perspectives that can be helpful to enhance gait recognition in a real-time environment.
8) We have also given a brief description of our proposed work.

After the introduction, the drafting of this article is as follows; section II, outlines the history of gait analysis. Section III, overview the gait recognition framework and also discuss performance measure parameters. Survey of gait databases outlined in section IV. Gait feature representation approaches defined in section V. Section VI, outlines short discussion on application domain of gait recognition. Section VII, represents research challenges that affect gait recognition in real time scenario. Future perspectives and conclusion discussed in section VIII and X and a short description of the proposed work outlined in section IX.

II. BACKGROUND OF GAIT ANALYSIS

This section provides information about the related work done in the field of behavioural biometric resource gait.

Human motion analysis delivers unprejudiced information that helps in the quantitative valuation of human movement. Quantitative evaluation infers a numerical outcome. In a quantitative analysis, the movement is examined numerically based on measurement, from the data collected during the movement. The advantages of quantitative analysis are that it provides a detailed, intent and accurate representation of the movement.

According to [10] human locomotion is the displacement of lower limbs under the stable state in which one lower limb serves as the support while the other lower limb helps in propulsion. The meaning of gait is related to the way and distinctiveness involved in a person's walking. Gait analysis is vital in several areas of biomechanics, robotics, sports

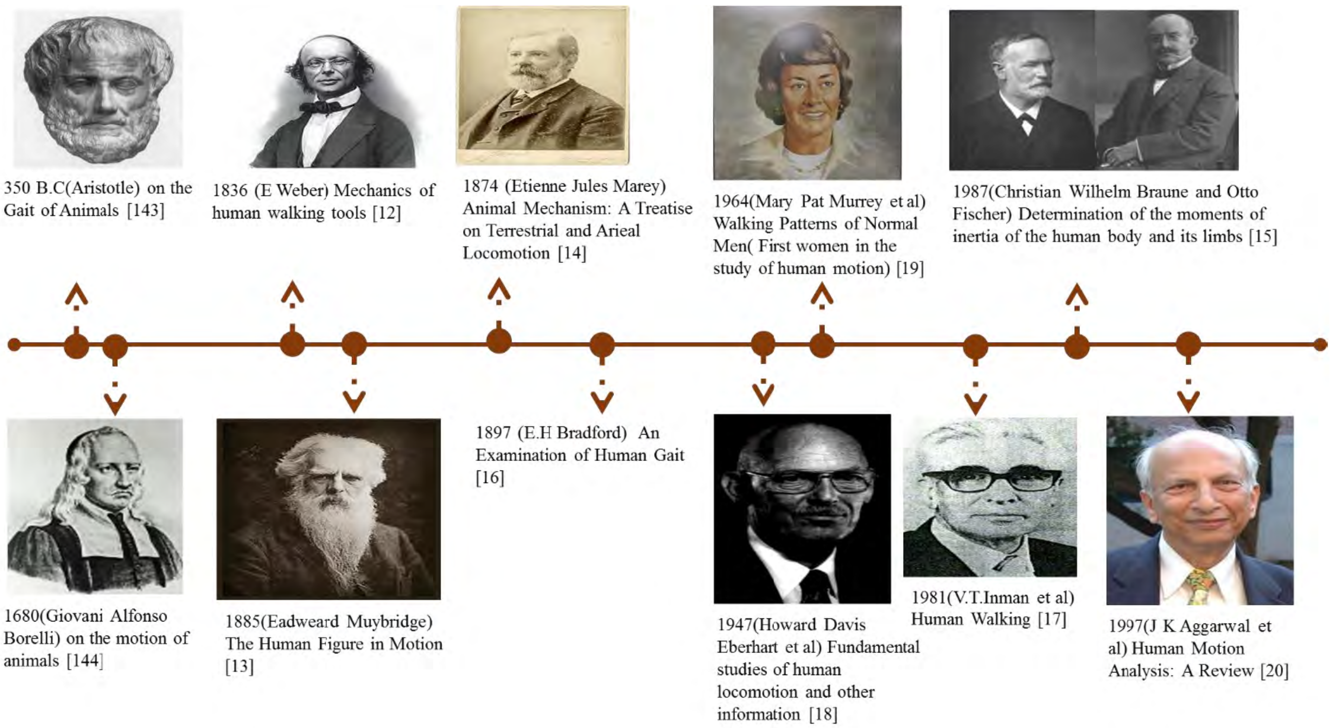

FIGURE 3. **Summarized the contribution of key authors in the history of human motion analysis. Some images in this figure and others are taken from the internet, and URLs are provided in appendix.**

analysis, rehabilitation, and gait disease diagnosis, video surveillance for security, identification, gender classification among others.

A. HISTORY OF HUMAN GAIT ANALYSIS

The motives behind studying the locomotion of human beings have changed over the centuries and gait has been a repeated preoccupation throughout history [11]. Even the Greek philosopher in the ancient age, Aristotle *et al.* (350 BC) [143] in ''on the Gait of Animals,'' analyzed and described human movement. They provide some relevant questions that form the basis of modern age to study human motion followed by Giovani Alfonso Borelli *et al.* (1680) [144] in the article ''On the Motion of Animals'' successfully depicts the muscular movement and body dynamics. They estimated the center of mass of men based on the rigid platform for analysis.

Human gait analysis was first analyzed by Weber and Weber (1836) [12] in ''Mechanics of human walking tools.'' They were the first to propose a quantitative model for the study of temporal and distance parameters of human locomotion based on the gait cycle. Englishman Muybridge (1885) [13] in ''The Human Figure in Motion'' and the Frenchman Marey (1874) [14] in ''Animal Mechanism: A Treatise on Terrestrial and Aerial Locomotion,'' was first to use photographic techniques for analysis of human movement patterns. Muybridge used a series of cameras to capture multiple pictures of both animals and human motion in rapid succession. Marey's studied on walking and research on muscular forces of a human being. Fig.3 presents the contribution of the key author's in the study of Human locomotion analysis.

Tridimensional mathematical based human gait analysis was first introduced by Braune and Fischer [15]. Their original work published during (1895-1904). Their study on the biomechanics of gait covered two transits, i.e., free walking and walking with a load. They study mass, volume and center of mass for three adult male and their body segments. Walking is the most fundamental function of all human activities, and there are variations in an individual's gait not only according to age, size, and strength but as an individual defined by Brandford (1897) [16].He experimented side view of human walking and depicts that angle formation of the foot with the ground varied between individuals and it is greater in long strides than in short strides during erect and the bent knee gait. Their study stated that human gait varied and classified in the inclined gait, an erect gait, the front foot gait, the heel gait, a rapid gait, the walking gait, and the running gait.

During 1950's of world war II, Inman *et al.* (1981) [17] and Eberhart and Inman (1947) [18], in a joint venture at University of California came up with an improved and tremendous resource of knowledge related to human locomotion for the treatment of world war veterans. The work had done during that period have set the foundation of many fundamental approaches that are now used for research analysis of human locomotion. During the end of World War II, Murray *et al*. (1964) [19], proposed a study to develop a simple, and inexpensive method of recording the displacements associated with locomotion of human being. She was the first researcher to measure the kinematics parameters of different body segments during walking in multiple planes. Their study provides standards for measurement and comparison of abnormal gait with a normal gait. Light photography camera was used to capture data for the study. Their research strongly proves that subjects between the age group of 60 to 65 have a shorter step and stride length and wider foot angle as compared to younger men. They found that subjects have consistent performance on different gait elements (such as step and stride length, stride width, and foot angle) and repeated walking trails.

Human gait analysis has been an open area of research for researchers for decades and has a broad spectrum of applications such as athletic performance analysis, surveillance, identification and medical disease diagnosis based on gait. In the twentieth century, Aggarwal and Cai [20] have a notable contribution to the study of human motion. They focused on three areas for interpreting human motion such as body parts involved in motion analysis, tracking human motion using single and multiple cameras and used image sequences for recognizing human activities.

B. OVERVIEW OF HUMAN GAIT

Gait activity between young and old healthy person achieved through the normal movement of both limbs. Research associated with gait analysis is the investigation of human walking patterns.

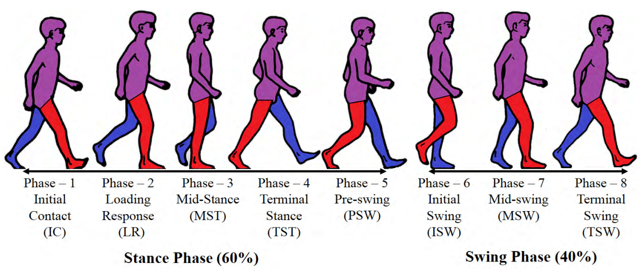

FIGURE 4. Phases of the gait cycle, right leg (red color) considered as a reference leg [10].

Walking is considered as a repetitious sequence of limb motion which help the body to move forward and formed gait cycle from heel strike(initial contact) to heel strike(terminal swing) as shown in Fig.4. Gait cycle is categorized into two periods' or phases namely stance and swing. One complete gait cycle is defined as stride. Perry and Burnfield [10] classified the gait cycle, into five stance phase periods and three swing phase periods as shown in Fig. 4. Stance phase begins with initial contact(IC) and covers 60% of the gait cycle. Swing phase covers 40% of the gait cycle and begins when the foot is lifted from the floor for limb advancement as shown in Fig.4. Step length defines the distance between the position of first foot contact with the ground and the same event done by the opposite foot. The step is defined as timing between the two limbs. Cadence is the number of footsteps per unit time, denoted as steps per minute. For healthy adult gait, cadence is 120 steps per minute [22]. Each limb performs three primary tasks that are weight acceptance (WA), single limb support(SLS) and limb advancement (LA) during each gait cycle, accompanied by eight motion patterns (means phases in gait cycle).

The importance of gait phase's analysis is to identify the impact of the different joint motions for each person gait patterns. Gait phases played a vital role in evaluating the concurrent action of individual joints, which helps in understanding the disability effects in human motion. Another significant feature of gait phases is that the joint motion of a person compared with others has variations in the phases. Therefore gait phases have functional importance in the analysis and classification of each person's gait pattern.

III. GAIT RECOGNITION SYSTEM

Study of gait locomotion is a traditional research area, which has been in progress during the ancient age by Aristotle (350 BC) approached by Giovani Alfonso Borelli (1680) in the renaissance period describing a systematic description of muscular movement and body dynamics. During the past decades, gait analysis has been widely investigated in the computer vision community and has proved promising outputs in areas like person recognition, gender classification, video surveillance, diagnosis of medical diseases which are related to gait like Parkinson disease, arthritis, cereal palsy and also beneficial for diagnosis of Chiropractic and Osteopathic, which causes delay in gait due to misaligned pelvic or sacru. Section VI, define three application areas of gait recognition namely gender classification, age recognition, and gait based clinical analysis.

As compared to other biometric traits, human gait has several unique features that have diverted the attention of computer vision researchers towards recognition of human based on gait. Gait features are classified into two approaches: model-based and model-free (also termed as appearance-based or Holistic approach by different researchers). Model-based gait system required the prior modelling of human body structure based on body components to obtain measurable parameters. Whereas, model-free gait system do not need prior modelling and operate directly on silhouette image after segmentation to generate gait features. The detail description and approaches proposed in recent years for model-based and model-free methods summarized in section V. Section A, give an overview of the general framework for gait recognition.

A. GAIT RECOGNITION FRAMEWORK

Gait recognition is an important and broader research area, which has invited more attention in recent years and can be applied in different applications like gender classification, human age classification, clinical analysis, action recognition, video surveillance monitoring. Gait recognition is a pattern analysis approach, in which different gait patterns of different users are examined and compared. The variations

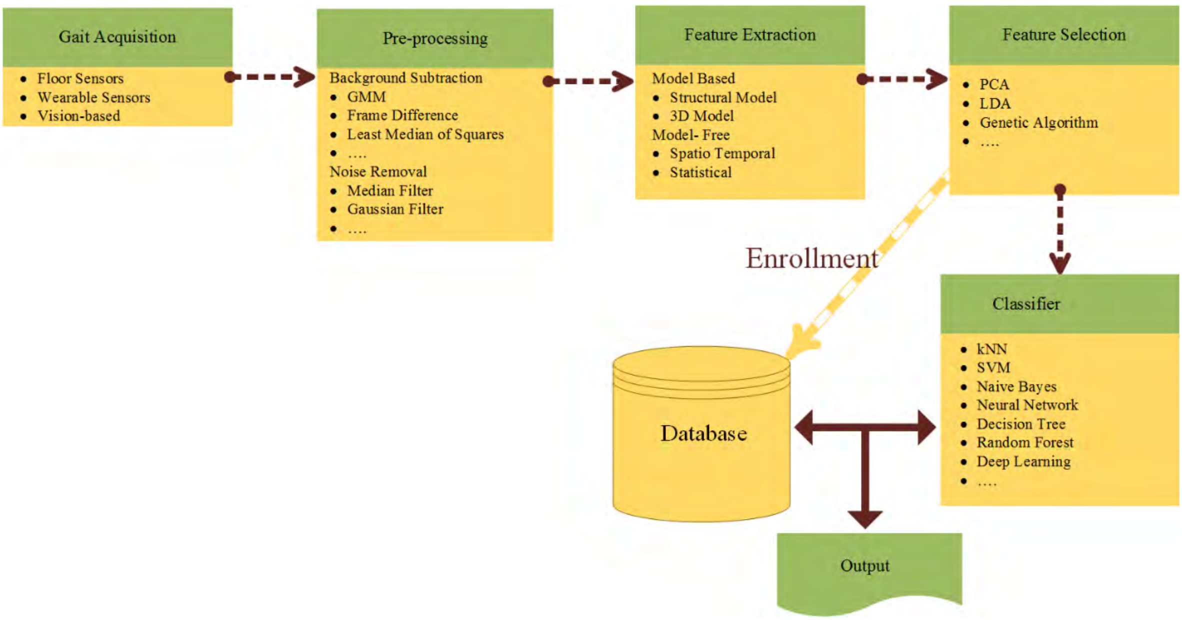

FIGURE 5. Generalized gait based recognition.

that exist between them are based on investigated parameters that differentiate the gait patterns of each person. The generic framework of automatic gait recognition system consists of different stages as shown in Fig. 5. The system has two phases, training or learning, and testing. In the training phase, first individual gait frames are captured and forwarded to the preprocessing stage for normalization to correct different geometric misrepresentation, noise reduction and object of interest segmentation. Then feature vectors of the region of interest are extracted, and an optimized feature vector is used to train the classifier. In the testing phase, test subject gait frames are passed through preprocessing to feature selection and then the trained classifier estimates the similarity measurement between the test frames (probe) with the trained frames (gallery) to give the desired output.

1) GAIT ACQUISITION

The first stage in gait recognition is to capture or detect subject gait frames, which is important because the accuracy of the system depends significantly on image samples used for training. The sensing devices have two categories: sensor-based and video based. Sensor devices are floor and wearable sensors [23]. Floor sensors are referred to as a pressure sensor, which generates pressure signals when a person walks on these sensors when placed on the specific floor [24], [25]. Wearable sensors are attached to different body joints, to collect different dynamic features (such as speed, acceleration, and position) and other information which can be used for gait pattern analysis. Commonly used wearable sensors include a light sensor (such as reflectors, moving lights), acceleration sensors, magnetic sensors, and gyroscopes. Sensor-based devices require more complex equipment's for collecting data, but although provides accurate data for analysis. Therefore, the most common application of sensor-based is in clinical research, such as Parkinson's disease diagnosis [26], [27]. Whereas video-based gait recognition research refers to capture specific human gait through the visual cameras that can be mounted at any location. These captured gait videos are processed to detect gait pattern information, which can be used for recognition. During the past decade, most research in the area of gait recognition is done using video-based gait dataset [2], [29], [40], [44], [53]. A detailed description of gait dataset created by the different organization is provided in section IV.

2) PRE-PROCESSING

In this stage background modelling of captured gait video has been accomplished to get the foreground object. Background subtraction methods are widely used for foreground object detection in gait recognition as in [28]

$$I_{f(i,j)} = \left|I_{o(i,j)} - I_{b(i,j)}\right| \tag{1}$$

Where $I_{o(i,j)}$ is the original image, $I_{b(i,j)}$ is the background image and $I_{f(i,j)}$ is the detected foreground image. Background modelling of video sequences is a critical task. Wang *et al.* [29] proposed a LMeds (least median of squares) method for background modelling to segment foreground object. Background modelling $bg_{(i,j)}$ based on LMeds is defined as

$$bg_{(i,j)} = \min_V \operatorname{med}_t \left(I^t_{(i,j)} - V\right)^2 \tag{2}$$

Where V represents the brightness score of background frame, which has to be estimated for location (i, j). I represent the sequence of frames in N frames; med is the median value with t index frames ranging within 1 − N.

Basic background subtraction method includes mean filtering, median method, frame difference method, statistical approach (Gaussian Mixture Model, support vector model), optical flow and many more. The motive of this process is to model human gait silhouette from which spatiotemporal shape and motion characteristics [31], [32], [130] are extracted for recognition.

3) FEATURE EXTRACTION

After the object of interest has been segmented from the background, features have been extracted that can be used for individual subject recognition. In gait recognition, features are extracted based on Model-based and Model-free (appearance based) representations. Detail description discussed in section V.

4) FEATURE SELECTION

In traditional gait recognition system, extracted features from pre-processed videos sequences are inadequate for classification and performance has been compromised. The reason is that high dimensional features may contain some unnecessary features. So, feature selection(or dimensionality reduction) approach can be applied, which is to choose a subset of variables(features) from the input features which efficiently describe the input variables while reducing effects of noise or extraneous variables and provide excellent prediction or classification results. Many feature selection approaches have been proposed, principal component analysis (PCA) [29] is a widely adopted dimensionality reduction method. Genetic Algorithm (GA) based feature subset selection proposed by Tafazzoli *et al.* [33] for gait recognition is another popular approach.

5) CLASSIFICATION

The last stage in gait recognition system is to classify the test gait sequences of an individual based on optimized features selected. Classification is divided into two categories: supervised and unsupervised. In table 2, we outline a list of classifiers that are used for gait recognition. The kNN(k nearest neighbor) is the most adopted classifier in gait recognition.

TABLE 2. Overview of the most adopted classifier in gait recognition.

Classifier	Studies	Benefits
kNN	[33][96][113][125][115][32] [126] [127][97][124] [103][37] [121][122]	Simple and efficient in computation, if training dataset is large
Navie Bayes	[33][97][129][120]	Very simple and easy to implement and fast because required less training data and make probabilistic predictions
SVM	[125][104][124][84]	Use kernels with the absence of local minima and achieve sparseness to the solution and capacity control achieved by optimizing the margins.
DCNN	[118]	Achieves high accuracy in recognition, but required good GPU for training and need many training data.

B. PERFORMANCE MEASURE IN GAIT RECOGNITION

Gait recognition system is a pattern recognition approach and attempts to capture two information's namely intra-class (entities in the same class) should have small variations (invariant information) and inter-class (entities in a different class), should have high variations (discriminating information). Based on these information gait recognition performance evaluation can be performed in two categories that are verification mode and identification mode [34]–[37]. Primary evaluation metrics used for evaluating gait recognition performance under verification and identification are: cumulative match characteristics (CMC), Rank order (Rank n identification rate, the receiver operating characteristic (ROC) curve, False match rate(FMR) also known as false acceptance rate(FAR), False non match rate(FNMR) also termed as false reject rate(FRR) and equal error rate(ERR).

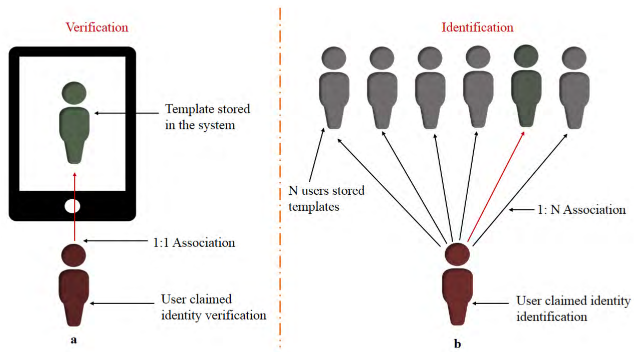

FIGURE 6. Working of verification and identification modes in the biometric system [138].

In identification mode, the system recognizes individual user gait signature with all the registered gait signatures in the system. Therefore, this mode has a 1:N association as shown in Fig. 6(b). Classification performance achieves through cumulative match characteristics or scores (CMC/CMS), which is based on Rank order (Rank n) identification rate. CMC or CMS implies the probability that the correct match is included in top n matches (that means 1:n identification, rank 1 or 5). The rank is plotted on x-axis while correct matches rate along the y-axis. A sample example of CMS curve taken from [36] is shown in Fig.7(a), here cumulative match scores were plotted between static features and dynamic features to show the performance of identification (for rank up to, $n = 20$). By analysing this graph they achieved correct classification rate for static features at rank = 1 (approx. 83%) and at rank = 5 (approx. 96%) while for dynamic features CCR at rank = 1 (approx. 87%) and at rank = 5 (approx. 99%).

The verification mode compares the identity of the claimed user with his/her identity previously registered or enrolled in the system. In such system 1:1 association is accomplished to determine whether the claimed identity is true or false

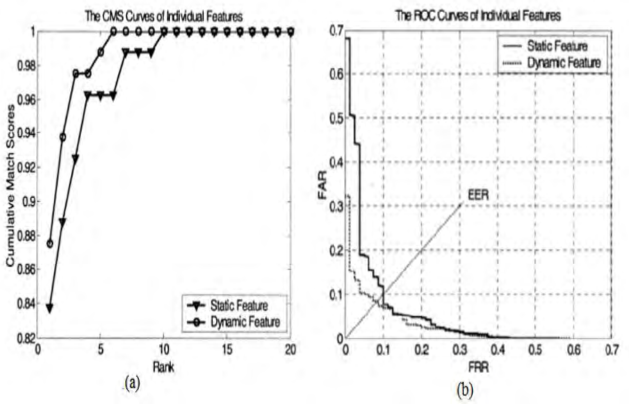

FIGURE 7. Single modality for correct identification and verification. (a) the CMS curve for Rank 1 to 20 and (b) tradeoff between FAR and FRR for static and dynamic features [36].

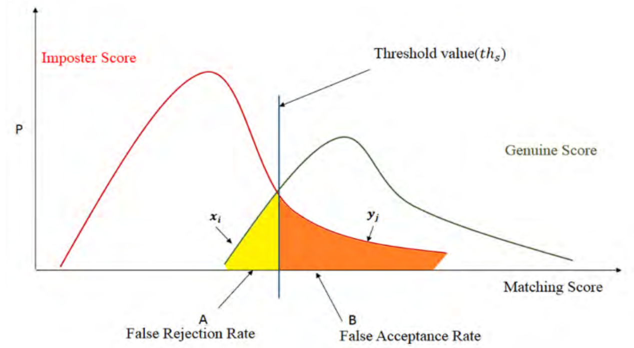

FIGURE 8. False acceptance and false rejection estimation based on the similarity score [142]. x_i is the set of genuine match and y_j is the set of non-genuine (imposter). Area A defines the rejection rate when the similarity score is less than the predefined threshold (th_s) area B implies the Acceptance Rate when Similarity score is greater then the threshold value th_s.

as shown in Fig. 6(a). Verification results are plotted through ROC. ROC is based on two error rates namely FAR or FMR termed as a type-1 error, and FRR or FNMR termed as a type-II error. Type-I Error implies that an error (in %) when an imposter is accepted as a genuine subject and Type-II Error implies that an error (in %) when rejecting a genuine subject to be an imposter. To analyze the performance of the model, ROC has been plotted for various pairs of FAR and FRR under predefined threshold values for acceptance as shown in Fig. 7(b) taken from [36] for two individual features (static and dynamic). Therefore, to evaluate the efficiency of gait recognition model in verification mode, ROC implies the trade-off between FAR and FRR. The closer it is to the origin the better will be the proposed model. Whereas, EER defines the rate at which FAR is equal to FRR and lower the EER better will be the gait recognition model.

Two matching scores, i.e., similarity measure and distance measure are used to estimate the distribution of false acceptance and false rejection error rate [142].

1) FAR AND FRR BASED ON SIMILARITY MEASURE SCORE

Let assume two sets of data samples, $X = \{x_1, x_2, \ldots, x_M\}$, represents the set of M genuine subjects and

$Y = \{y_1, y_2, \ldots, y_N\}$, represents the set of N imposters. Then, FAR and FRR based similarity score defined as

$$\mathrm{FAR}\,(\mathrm{th_s}) = \frac{1}{\mathrm{N}} \sum_{\mathrm{j=1}}^{\mathrm{N}} 1\left(\mathrm{y_j} > \mathrm{th_s}\right) \tag{3}$$

$$\mathrm{FRR}\,(\mathrm{th_s}) = \frac{1}{\mathrm{M}} \sum_{\mathrm{i=1}}^{\mathrm{M}} 1\,(\mathrm{x_i} \leq \mathrm{th_s}) \tag{4}$$

Where $1\left(\mathrm{y_j} > \mathrm{th_s}\right)$ states that how many subjects in Y (imposter) are greater than a predefined threshold based on the similarity score $\mathrm{th_s}$. $1\,(\mathrm{x_i} \leq \mathrm{th_s})$ states that how many genuine subjects in X set are below the threshold ($\mathrm{th_s}$). The distribution graph of FAR and FRR based on similarity measure is shown in Fig. 8.

2) FAR AND FRR BASED ON DISTANCE MEASURE SCORE

Let assume X & Y be two data set of genuine and imposter subjects as defined above. Then, FAR and FRR based distance score defined as:

$$\mathrm{FAR}\,(\mathrm{th_d}) = \frac{1}{\mathrm{N}} \sum_{\mathrm{j=1}}^{\mathrm{N}} 1\left(\mathrm{y_j} \leq \mathrm{th_d}\right) \tag{5}$$

$$\mathrm{FRR}\,(\mathrm{th_d}) = \frac{1}{\mathrm{M}} \sum_{\mathrm{i=1}}^{\mathrm{M}} 1\,(\mathrm{x_i} > \mathrm{th_d}) \tag{6}$$

Where $1\left(\mathrm{y_j} \leq \mathrm{th_d}\right)$ states that how many subjects in Y (imposter) set are less than the threshold $\mathrm{th_d}$, where $\mathrm{th_d}$ is the predefined threshold based on distance score. $1\,(\mathrm{x_i} > \mathrm{th_d})$ shows that the number of genuine subjects in X are greater than threshold $\mathrm{th_d}$. Distribution graph of FAR and FRR based on distance measure is shown in Fig. 9.

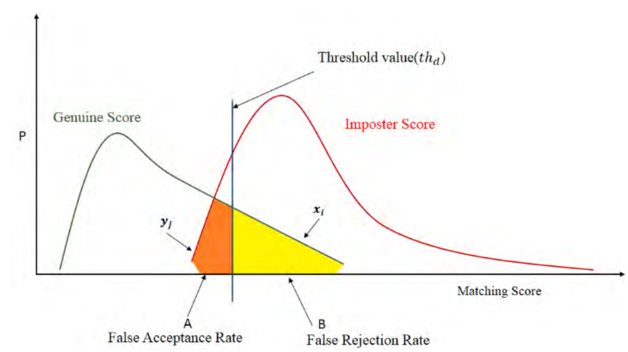

FIGURE 9. The figure implies false acceptance and false rejection estimation based on Distance score [142]. x_i is the set of genuine match and y_j is the set of non-genuine (imposter). Area A defines the acceptance rate when distance score is less than the predefined threshold value (th_d) and area B implies the rejection rate when Distance score is greater than the threshold value th_d.

Gait recognition can be an essential application in visual surveillance because of recognizing a subject from a long distance. So, some other relevant metrics help in evaluating the performance of any detection algorithm in video surveillance scenario may be described as:

TABLE 3. Shows year wise creation of vision based dataset. Acronym of words used in table: model-free(MF), model-based(MB), indoor(I), outdoor(O), floor(F), treadmill(T), concrete(C), ground(G).

S. No.	Dataset	Ref./year	No. of Subjects	No. of Seq.	Gender Ratio (M/F)	Covariate Conditions	Env.	Surf.	Frame Rate /Size	Resource	MF	MB
1	Kyushu University, KY4D Database-B: Curve Walk	Iwashita et al. [53] / 2014	42	168	-	3 view directions : frontal view(~ 0^o), side view(~ 45^o) and side view(~90^o)	I	F	-	16 cameras	✓	
2	Kyushu University, KY4D Shadow Database	Iwashita et al. [54] / 2014	54	324	-	Carrying bag, cloth variations	I	F	-	2 infrared light, 1 camera	✓	
3	OUISIR Speed Transition (GaitST)	Lu et al. [44] / 2014	179	-	-	Speed transition, acceleration speed (1km/h to 5km/h),deceleration speed (5km/h to 1km/h)	I	F,T	60fps / -	1 camera	✓	
4	Cleveland State University, Human Motion & Control Lab	Moore et al. [65] / 2014	15	-	11/4	5 walking variations	I	T	-	10 osprey cameras, 47 markers		✓
5	Korea Institute of Science & Technology , KIST	Yun et al. [64] / 2013	113	-	50 / 63	8 multiview variations with constant speed (3km/h)	I	T	- / -	8 cameras, 15 markers		✓
6	OUISIR Large Population (OULP)	Iwama et al. [40] / 2013	4007	-	2135 / 1872	-	I	F	30fps / 640x480	2 cameras	✓	
7	University of Cordoba, AVA-Multiview	Fernandez et al. [55] / 2013	20	1200	16 / 4	Multiview conditions	I	F	25fps / 640x480	6 cameras	✓	
8	Indonesian Gait Database	Mahyuddin et al. [57] / 2012	212	-	102 / 110	5 conditions: view variations, carrying condition, surface, shoe type and time	I	F	90fps / -	LED markers, 1 video camera		✓
9	OUISIR Treadmill (OUTD) Speed Variation	Makihara et al. [39] / 2012	34	-	-	Speed variations (2km/h to 10 km/h), 32 cloth combinations ,25 view variations, Gait fluctuation	I	T	60fps / 640x 480	25 cameras	✓	
	Cloth Variation		32	2746	-							
	View Variation		200	-	100 / 100							
	Gait Fluctuation		185	370								
10	Kyushu University, KY4D Database-A: Straight Walk	Iwashita et al. [52] / 2010	42	168	-	3 view directions : frontal view(~ 0^o), side view(~ 45^o) and side view(~90^o)	I	F	-	16 cameras	✓	
11	TUM-IITKGP	Hofman et al. [61] / 2010	35	840	-	Occlusion(dynamic and static), carrying conditions, 4 walking variations	I	F	-	1 camera	✓	
12	CASIA Dataset B	Yu et al. [46] / 2005	124	13640	93 / 31	11 view variations, clothing variations and carrying conditions	I	F	25fps / 320x240	11 cameras	✓	
13	CASIA Dataset C	Tan et al. [47] / 2005	153	1530	130 / 23	4 walking variations : normal ,slow, fast and normal with bag	O	C	25fps / 320x240	Infrared cameras	✓	
14	CASIA Dataset A	Wang et al. [29] / 2001	20	240	-	3 view variations : laterally 0^o, obliquely 45^o, frontally 90^o	O	C	25fps / 352x240	Panasonic digital camera	✓	
15	University of south Florida, HID-USF	Sarkar et al. [48] / 2001	122	1870	-	5 covariate conditions: 2 shoe type, 2 carrying condition, 2 surface type, 2 viewpoints, 2 different time instants	O	C,G	30fps / 720x480	2 cameras	✓	
16	CMU Motion of Body(Mobo)	Gross et al. [59] / 2001	25	600	-	4 walking patterns : slow, fast, incline, walk with ball	I	T	30fps / 640x480	Sony DXC 9000's camera	✓	
17	HID-Georgia Tech.	Johnson et al. [62] / 2001	20	188	-	3 view variations	I,O	F	30fps / 320x240	3 cameras	✓	
18	HID-UMD Database-1 http://www.umiacs.umd.edu/labs/pirl/hid/data.html	- / 2001	25	100		4 view variations	O	C	-	1 camera	✓	
19	HID-UMD Database-2 http://www.umiacs.umd.edu/labs/pirl/hid/data.html	- / 2001	55	220	-	T shape pathway	O	C	-	2 camera	✓	

TABLE 3. *(Continued.)* **Shows year wise creation of vision based dataset. Acronym of words used in table: model-free(MF), model-based(MB), indoor(I), outdoor(O), floor(F),treadmill(T),concrete(C), ground(G).**

S. No.	Dataset	Ref./year	No. of Subjects	No. of Seq.	Gender Ratio (M/F)	Covariate Conditions	Env.	Surf.	Frame Rate /Size	Resource	MF	MB
20	HID-UMD Small Dataset http://www.umiacs.umd.edu/labs/pirl/hid/data.html	- / 2001	12	-	-	5 view variations: $0^o, 15^o, 30^o, 45^o, 60^o$	O	C	-	-	✓	
21	SOTON , Small Dataset http://www.gait.ecs.soton.ac.uk/database/small_db.php3	- / 2001	12	-	-	5 shoe variations, 3 cloth variations, 3 speed variations, view variation with bag	I	F	25fps / 384x288	1 camera	✓	
22	SOTON, Large Dataset http://www.gait.ecs.soton.ac.uk/database/large_db.php3	- / 2001	115	2128	-	6 view variations: normal track + treadmill, oblique track + treadmill	I,O	F,T	25fps / 720x576	2 cameras	✓	
23	University of California , UCSD	Little et al. [63] / 1998	6	42	-	1 view direction: fronto parallel	O	C	30fps / 640x480	1 Sony Hi8 video camera	✓	

- True Positive(TP): number of correct detection by the system
- False Positive(FP): number of false detection by the system
- False Negative(FN): number of positive objects incorrectly missed by the system
- True Negative(TN): number of correct nondetection by the system
- Precision (P): Positive predictive value:

$$P = \frac{TP}{FP + TP} \tag{7}$$

- Recall (sensitivity) (R): Probability of detection:

$$R = \frac{TP}{FN + TP} \tag{8}$$

- Specificity (SP):

$$SP = \frac{TN}{TN + TP} \tag{9}$$

- F-Measure (F-Score): Measure of test accuracy:

$$F = \frac{2 * P * R}{P + R} \tag{10}$$

  The harmonic mean of precision and recall
- CCR (Correct Classification Rate):

$$CCR = \frac{\text{Number of correct classified}}{\text{Total number of subjects}} \times 10 \tag{11}$$

IV. GAIT RECOGNITION DATASETS

Fundamental success and development of a new application rely on the database. To test and develop a robust gait recognition model requires a database of sufficient size and variant factors. In recent years more and more dataset dedicated to human gait recognition have been created considering various factors such as shadow, view variations (single and multiview using number of cameras), clothing factor, carrying conditions, shoe type, variable walking surface conditions(treadmill, floor, grass, concrete surface, incline), acquisition environment (indoor, outdoor). A systematic description of each gait recognition dataset created since 1998 is summarized in table 3 & 4 based on taxonomy shown in Fig.10. Total 33 gait dataset are summarized, out which 23 are a vision based and remaining are sensor based. The most state-of-art literature considered in this article is based on the vision-based dataset.

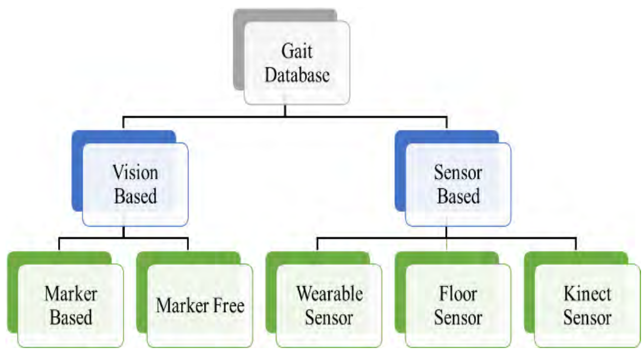

FIGURE 10. **Suggested taxonomy of gait dataset.**

A. VISION BASED GAIT DATABASE

In recent years focus of research on gait recognition is based on vision-based gait dataset. Table 3 gives the summary of marker-based (MB) and marker-free (MF) vision based gait dataset. Out of 23, only 3 datasets are MB, which shows that approx 90% of the research focus in gait recognition is based on the MF dataset. Usage ratio of vision based gait dataset for research analysis defines in Fig. 11 based on publications from 2012 to July 2018. The CASIA-B dataset is the most adopted dataset for analyzing the proposed models for gait recognition. The reason is that CASIA-B dataset has a

TABLE 4. Shows year wise creation of sensor based gait dataset. Acronym of words used in table: Kinect sensor (KS), floor sensor (FS), wearable sensor (WS), indoor (I), outdoor (O), floor (F), treadmill (T), concrete(C).

S. No.	Dataset	Ref./year	No. of Subjects	No. of Seq.	Gender Ratio (M/F)	Covariate Conditions	Env.	Sur.	Frame Rate/Size	Resource	KS	FS	WS
1	OUISIR- OULP Bag β	Makihara et al. [45] / 2017	2070	2068	-	Carrying condition	I	F	-	3 IMUZ sensors			✓
2	Halmstad University, MAREA	Khandelwal et al. [58] / 2017	20	-	-	Speed variations: 4km/h – 8km/h with 0.4km/h increment	I,O	F,T,C	-	Treadmill, shoes with piezo-electric force sensitive resistors, accelerometer		✓	✓
3	Shandog university, Kinect dataset	Wang et al. [83] / 2016	52	1040	28 / 24	7 view variations: 0°,90°,135°,180°,225°,270°, arbitrary angle	I	F	-	2 Kinect sensor	✓		
4	OUISIR Similar Action Inertial Sensor Dataset	Ngo et al. [50] / 2015	460	-	-	Ground conditions: flat ground, up/down stairs, up/down slope	I	F	-	3 IMUZ sensors			✓
5	Zhejiang University, ZJU-GaitAcc	Zhang et al. [56] / 2015	175	-	-	5 gait acceleration series	I	F	-	ADXL330 triaxial accelerometer			✓
6	OUISIR Inertial Sensor Dataset	Ngo et al. [49] / 2013	744	-	389 / 355	Ground conditions: level walk, up & down slope, sensor location variations	I	F	-	3 IMUZ sensors			✓
7	University of Patras, UPCV	Kastaniotis et al. [60] / 2013	30	150	15 / 15	Normal walk in straight line	I	F	-	Kinect sensor	✓		
8	TUMGAID	Hofmann et al. [133] / 2012	305	3370	-	Time duration(months), carrying conditions, shoe variations, side view, top-down view	I	F	30 fps / 640x480	Kinect sensor, 4 microphones	✓		
9	University Autonoma de Barcelona, DGait	Borras et al. [51] / 2012	53	583	36 / 17	4 view variations : right diagonal, left diagonal, side view, frontal view	I	C	30 fps / 640x480	Kinect sensor	✓		
10	CASIA Dataset D	Zheng et al. [25] / 2009	121	-	-	Walking speed effects, shoe variations	I	F	-/ 40x90	RScan USB pressure sensor		✓	

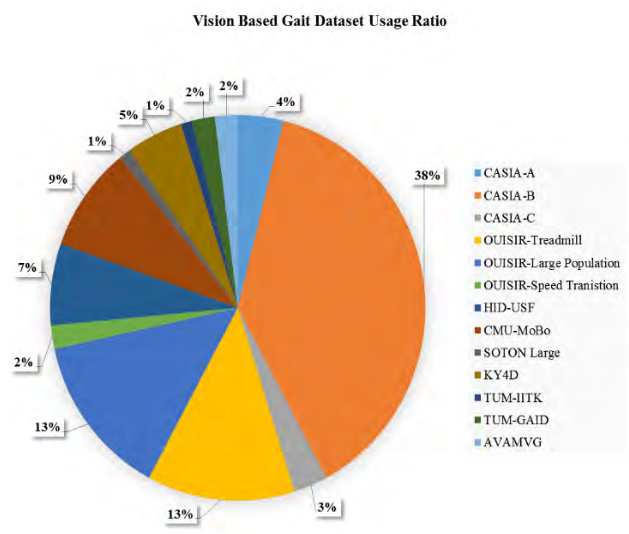

FIGURE 11. Describes the usage ratio of the most adopted vision based gait dataset.

collection of 124 subjects with 11 view variations along with clothing and carrying covariate conditions which affect gait recognition performance.

Osaka University (OUISIR) has a large collection of gait database considering different covariates conditions (such as view variation, clothing variation, carrying condition, and speed transition). Currently, they have a dataset of 4007 subjects [40]. Chinese Academy of Sciences (CASIA) has different categories of the dataset (dataset-A, dataset-B, dataset-C, and dataset-D). CASIA dataset-B [47] has a collection of 124 subjects considering 11 view directions with an interval of 18° each. This dataset also focuses on clothing variations and carrying conditions which affect gait recognition performance.

B. SENSOR BASED GAIT DATABASE

Sensor-based gait dataset captures the behavioral signals of human motion. These signals are translated into quantitative data that can be evaluated by the computer system.

Inertial sensor-based gait dataset first created by OUISIR [49]. The benefit of this dataset is that it considers 3 slope conditions: level walk, up-slope and down-slope walk. This dataset has 744 subjects with age ranging from 2 to 78 years. Ground reaction forces can be used for distinguishing human gait patterns during the gait cycle. Pressure sensor based gait data created by CASIA [25]. They employed RScan USB pressure sensor on the floor of size 3m x1m to capture foot pressure data. Total 13000 images were captured from 121 subjects. They considered two different conditions: walking speed effects and different shoe type conditions.

Model-based gait recognition has an issue of view variation and self-occlusion. In recent years, Kinect sensors have been used to tackle these issues. Kinect sensor builds a 3D skeleton

TABLE 5. Model-based approaches based on approaches for gait recognition with accuracy rate.

S. No.	Reference/ Year	Technique/ Approach	Gait Parameters/ Features	Dataset	Evaluation / Classifier	Accuracy(%)
1	Bobick et al. [67] / 2001	Parametric Method	Static body parameters. Stride parameters.	Recorded 18subjects gait data in open indoor. Two view angle: 45, frontal parallel. Recorded 15 out of 18 in outdoor with shadow.	kNN	Height + stride : 49% Single stride : 21%
2	Abdelkader et al. [66] / 2002	Parametric Method	Height and stride parameters.	Created 45 subjects gait data: 7 females , 28 males	-	-
3	Yoo et al. [71] / 2008	2D Stick Figure	Trajectories based kinematic characteristics(Linear and angular position, displacement and time derivation).	Southampton HID database, 100 subjects	BPNN	Training vector:150 Testing vector: 30 CCR : 90% , Good Training vector:150 Testing vector : 30, CCR: 83.3% , Fair Training vector:150 Testing vector : 30 CCR: 83.3% , Bad
4	Yoo et al. [72] / 2011	2D Stick Figure	Motion parameters(cycle time and gait speed).	-	k-NN	Subject: 30 k=1:96.7% , k=3:93.3% k=5:96.7% Subject:60 k=1:91.7% , k=3:86.7% k=5 : 85.7% Subject: 100 k=1:84.0% , k=3:80.0%, k=5:82.0%
5	Wagg et al. [73] / 2004	Hierarchical shape	Joint rotations(hip, knee,and ankle). Static parameters. Total 45 parameters.	HID database : 115 subjects	NN+ ANOVA	Indoor : ≈ 84% Outdoor : ≈ 64%
6	Bouchrika et al. [74] / 2014	Haar Template Matching	Gait kinematic features.	CASIA Dataset- B	k-NN	73.60%
7	Bouchrika et al. [75] / 2015	Elliptic Fourier Descriptor	Angular measurement of legs. Spatial displacement of the body trunk.	Southampton indoor gait database 20 subjects, 120 sequences	-	86.67%
8	Bouchrika et al. [76] / 2007	-	Static and dynamic features.	Southampton HID database 120 subjects	-	92%
9	Tafazzoli et al. [77] / 2010	Active Contour Model	Kinematic features.	Georgia Tech database 20 subjects	-	With arm feature : 94.5% Without arm feature : 93.1%
10	Yam et al. [68] / 2003	Forced coupled oscillator pendulum model	Thigh and leg motion features.	Created 20 subjects gait data (walking and running) on a treadmill	kNN	k=1 walking : 80% Running : 90%
11	Gu et al. [78] / 2010	3D gait model	Configuration features (whole body joints). Lower limb features	Xmas Motion Acquisition Sequences (IXMAS). 12 subjetcs (walk- incricle)	MAP	Rank 1 Trainig test: 100% Validation test: 97.9% Testing test: 94.1%
12	Zaho et al. [79] / 2006	3D gait model	Static features(length of key segments). Dynamic features(motion trajectories of lower limb).	CMU MoBo database25 subjects - slow walk for the trainingset - inclined walk for the test set	LTN for matching and recognition	Static + dynamic : 70%
13	Kwolek et al. [81] / 2014	3D gait model	Spatio-temporal feature descriptor	Created 22 subjects gait database	NB MLP LSVM	Rank 1: 93.5% for SVM Rank 3: 99.6 %for SVM
14	Urtasun et al. [82] / 2004	3D gait model	Temporal motion parameters	Created 4 subjects gait using Vicon optical motion system: 2 male and 2 females. 9 walking speed (3Km/h to 7 Km/h).	k-means Mahalanobis distance	N/a
15	Krzeszowski et al. [80] / 2013	3D gait model	Tensorial gait data	Created 22 subjects gait database : straight walking, diagonal walking.	NB MLP	NB : 85% MLP : 90%
16	Wang et al. [83] / 2016	3D gait model	Static features (the length length between skeleton). Dynamic features(angle between skeleton).	Created 52 subjects gait dataset using Kinect V2 tool.	NN	Static + dynamic features 0^0 : 94.23% 90^0 : 90.38% 135^0 : 90.38% 225^0 : 88.46% 270^0 : 92.31%
17	Fernandez et al. [84] / 2016	3D voxel	3D dynamical features of a gait	AVA MultiviewDataset KY4D Gait Dataset	SVM PCA+LDA k-fold cross validation	≈ 100%
18	Kim et al. [69] / 2009	Silhouette Template matching	Active shape features	HumanID gait challenge dataset(HGCD). Considered covariates: viewpoint, shoe,	Prediction- based hierarchical ASM	Identification Rate : view : 97% , shoe : 95% ,

TABLE 5. ***(Continued.)*** **Model-based approaches based on approaches for gait recognition with accuracy rate.**

S. No.	Reference/ Year	Technique/ Approach	Gait Parameters/ Features	Dataset	Evaluation / Classifier	Accuracy
				viewpoint + shoe, surface, shoe + surface, viewpoint + surface, viewpoint + shoe + surface.		view + shoe : 91% , surface : 92% , sjoe +surface : 86% , view + surface : 85% , view + shoe + surface : 78%
19	Zeng et al. [70] / 2013	Deterministic learning	Silhouette lower limb joint angles	CASIA dataset A CASIA dataset B	RBF neural network	CASIA- A : 92.5% CASIA - B : 91.9%
20	Zhang et al. [85] / 2010	Dual gait generative model	Kinematic gait features. Visual gait features. Dynamic gait features.	Carnegie Mellon University (CMU Mocap) for training. Brown HumanEva for testing.	n/a	Single gait without mapping EER : 102.77 Single gait with mapping, EER : 32.20
21	Kastaniotis et al. [86] / 2015	Pose estimated gait representation model	Dynamic features	Created 30 subjects gait data using Microsoft Kinect Sensor : 15 females, 15 males. Straight direction.	kNN	Identification Rate : 93.20%. EER on verification: 3.1%. Gender Recognition Rate: 99.11%
22	Yoo et al. [87] / 2002	Trigonometric polynomial approach	Trajectory-based kinematic features	Created 4 subjects indoor gait database	BPNN	Number of Features : 7 Recognition Rate Avg : 100% Min : 100% Number of Features : 5 Recognition Rate: Avg : 88.6% Min : 80% Number of Features : 3 Recognition Rate Avg: 65.7% Min : 60%
23	Rawesak et al. [88] / 2001	Trajectory-based gait motion estimation	Dynamic features(lower body- hip & knee, joint angle trajectories)	Created gait database using Ascension electro-magnetic motion capture system Database I: 18 subjects, 106 walks Database II : 8 subjects , 84 walks Database III : 8 subiects . 96 walks	NN Euclidean distance	Recognition Rate: Database I : 73% Database II : 42% Expected Confusion No. Database I : 0.097 Database II : 0.15 Database III : 0.27
24	Goffredo et al. [89] / 2010	Trajectory-based gait motion estimation	Dynamic features (angular motion and trunk spatial displacement)	SOTON dataset : indoor, 20 subjects. CASIA-B dataset : 6 view directions (36^0,540, 72^0, 90^0,108^0,126^0).	kNN leave-one-out cross validation rule	SOTON : 95.8% CASIA-B : Avg. : 73.6%
25	Chen et al. [90] / 2016	Hypergraph partition approach	3D tensor gait features	Created 120 subjects multi-gait dataset with 2~4 participant. 1440 videos walking alone. 720 double pedestrians 480 three pedestrians gait videos. 360 four pedestrians gait videos. Two View-point considered : frontal , lateral	NN	Recognition Rate 2 participant frontal : 89.2% lateral : 80.3% 3 participant frontal : 88.3% lateral : 78.2% 4 participant frontal : 87.2% lateral : 76.5%
26	Choudhary et al. [130] / 2013	Fusion of Spatio-temporal+ statistical + physical (STM-SPP)	Shape features based on Procrustes shape analysis + elliptic Fourier Descriptor. Spatio-temporal motion features. Physical features.	CMU MoBo Dataset. HumanID Gait Challenge.	z normalized similarity score Rank based classifier	Identification Rank-1 : PSA : 84% Combination classifier : 92% Verification PSA- 86%, False Alarm Rate : 1% Combined Classifier:94%, False Alarm Rate : 1%

of joints [83]. Kinect sensors can be used for clinical diagnosis of diseases based on gait [109]. We outline 4 organizations Kinect sensors based gait dataset, which has considered different covariate conditions (such as view variations, carrying conditions, and shoe variations).

The dataset summarized in table 3 & 4 can be applicable to surveillance monitoring, recognition, motion analysis, clinical analysis, sports analysis, rehabilitation and many more.

V. GAIT RECOGNITION APPROACHES

There are two broad categorized approaches to represent and extract gait recognition features, i.e., Model-based and Model-free.

A. MODEL-BASED APPROACHES

In this section, we examine the various model-based gait recognition approaches proposed in the state-of-art studies. Table 5 summarizes model based gait recognition approaches based on the techniques employed, with the accuracy rate and have also outlined the features used for gait recognition along with classifier used. Modeling of human body or motion in a model-based approach is explicitly based on the extracted prior information. In this method, gait signatures are derived by modelling or tracking of body components (such as limbs, legs, arms, and thighs), which are employed for identification or verification of an individual. In the model-based method, a model of the human body (such as structural

TABLE 6. Model free approaches based on approaches with their accuracy rate.

S. No.	Reference/ Year	Technique/ Approach	Gait Parameters/ Features	Dataset/ Covariates	Classifier / Evaluation	Accuracy (%)
1	Sundaresan et al. [91] / 2003	Temporal Template	Hidden Markov Model (HMM) features.	USF database : 75 subjects. 4 covariate conditions : grass (G), concrete(C) , shoe type (A,B) camera view (L,R)	3 distance matrices : Euclidean distance , Inner product(IP) distance, Sum of absolute difference(SAD) distance. 7 Probe Conditions : A(GAL) B(GBR),C(GBL),D(CAR),E(CBR) F (CAL),G (CBL) A (GAL): grass(G), shoe type(A), view left(L). G (CBL) : concrete(C), shoe type(B), view left(L).	Rank 1 Probe, Distance Matric IP Euclid SAD A 99% 99% 98% B 89% 89% 89% C 78% 78% 75% D 36% 29% 23% E 29% 28% 21% F 24% 19% 16% G 18% 14% 15% Rank 5 Probe, Distance Matric IP Euclid SAD A 100% 100% 100% B 92% 92% 92% C 92% 92% 92% D 62% 60% 59% E 54% 54% 59% F 47% 46% 44% G 48% 48% 45%
2	Havasi et al. [92] / 2006	Spatiotemporal Method	Symmetry features.	1000 samples : 300 walking, 700 non-walking. 2 classes : waking ,non- walking.	Kernel FisherDiscriminant Analysis(KFDA)	Detection Rate 97% False +ve : 1.25 False –ve: 1.15
3	Boulgouris et al. [93] / 2005	linear time normalized method	Silhouette features. Angular features.	HumanID Gait Challenge. 7 probe condition : view, shoe, shoe + view, surface, surface + shoe, surface + view , surface + view+ shoe	Linear Discriminant analysis Cumulative Match Score	Identification Rate Rank 1 Rank 2 Sf Af Sf Af 94% 89% 99% 99%
4	Wang et al. [99] / 2002	Statistical shape analysis	Procrustes shape analysis method to extract shape signature features.	NLPR(CASIA-A) Dataset 3 view angle : 0^0, 45^0, 90^0	Background Subtraction: LMedS Classifier : NN, kNN , ENN	k=1 (NN) 0^0:71.25% ,45^0: 72.5% , 90^0: 81.25% k=3 (kNN) 0^0 : 72.5% , 45^0: 73.75 %, 90^0 : 80 % ENN 0^0 : 88.75%, 45^0 : 88.75% , 90^0 : 90%
5	Wang et al. [36] / 2004	Statistical shape + model-based analysis	Static features(Procrustes Mean shape distance). Dynamic feature (joint angle lower limbs).	Created dataset of 20 subjects. Total 80 sequences.	ENN Rank-summation Score-summation Equal Error Rate	Features : Rank 1 , Rank 3 SF : 83.75%, 92.5% DF : 87.5% , 97.5 % Features : EER SF:10 , DF:8.42
6	Kusakunniran et al. [32] / 2014	Spatio Temporal Domain	Space-time interest points (STIP)	CASIA dataset B. Covariates :carrying bag , view variations, wearing coat.	Nearest Neighbor Leave-one-out cross-validation	Avg. : 63.6%
7	Rida et al. [95] / 2015	Gait Energy Image(GEI)	Divide GEI into two parts. Two features : bottom a row of x as features, top row of y as features.	CASIA dataset B . Covariates : carrying bag , view variations, wearing coat.	Phase-only correlation	81.40%
8	Sarkar et al. [48] / 2009	Gait Entropy Image (GEnI)	Static and Dynamic features	CASIA dataset A,B & C. SOTON small dataset .	Adaptive component and discriminant analysis(ACDA)	GEnI + ACDA CASIA : 55.5 SOTON : 54.5
9	Nandy et al. [97] / 2016	Statistical GEI	Statistical shape features from GEI edge contour.	OU-ISIR Treadmill dataset. Covariates: clothing condition.	Classifier : kNN , Navie Bayes , Decision Tree. Random Forest. Intra cloth variation : F-statistics. Inter-subject distance : t- statistics. Intra-class correlation (ICC).	Grid segmented features : 83.30% Combination of features : 79%
10	Rida et al. [96] / 2016	Group lasso GEI	Segment GEI to extract discriminative features.	CASIA dataset B. Covariates : carrying bag, clothing varations,view variations wearing coat.	Canonical discriminant analysis. Principal component analysis. Multiple discriminant analysis.	Normal conditions : 98.39% Carrying conditions :75.89% Clothing conditions : 91.96% Overall : 88.75% Standard deviation : 11.59

TABLE 6. ***(Continued.)*** **Model free approaches based on approaches with their accuracy rate.**

S. No.	Reference/ Year	Technique/ Approach	Gait Parameters/ Features	Dataset/ Covariates	Classifier / Evaluation	Accuracy (%)
11	Wang et al. [98] / 2012	Chrono Gait Image (CGI)	The contour of silhouette images.	USF Human ID Gait Challenge. CASIA dataset B. Soton Large database. Covariates : carrying bag, clothing variations.	Nearest neighbor classifier(NN) Principal component analysis Linear Discriminant Analysis	Rank 1 : 61.69% Rank 5 : 79.12%
12	Shutler et al. [131] / 2006	Statistical features based on moments	Zernike velocity moment features. Two image sets : spatial templates(ST) and temporal templates(TT).	CMU dataset : 20 subjects. 4 covariates :slow walk, fast walk, normal view, oblique view. SOTON : 50 subjects	k nearest neighbor classifier leave one out rule for validation	Feature Space : ST+TT k=1 : 95% , k=3 : 93% Feature Space : ST k=1 : 61.87% , k=3 : 49.5% Feature Space : TT k=1 : 46.16 % , k=3 : 35.16%
13	Wang et al. [100] / 2002	Statistical principal component analysis	Eigen transformation for silhouette shape features.	Created database of 7 subjects.	Nearest neighbor classifier(NN) Similarity measure: spatiotemporal correlation (STC), normalized euclidean distance (NED)	STC : 90.5 % NED : 89.3 %
14	Abdelkader et al. [101] / 2002	Physical Parameter	Spatiotemporal features : stride length and cadence	17 subjects gait data: 360*240 / 30fps.	Rank order statistic leave one out rule for validation	False Acceptance Rate : 11% CCR ~ 89%
15	Collins et al. [102] / 2002	Physical parameter	Shapes features: body height,width,body part proportions. Gait parameters: stride length and amount of arm swing.	CMU Indoor Treadmill MIT Indoor Floor UMD Outdoor ground USH Indoor floor	Nearest neighbor	

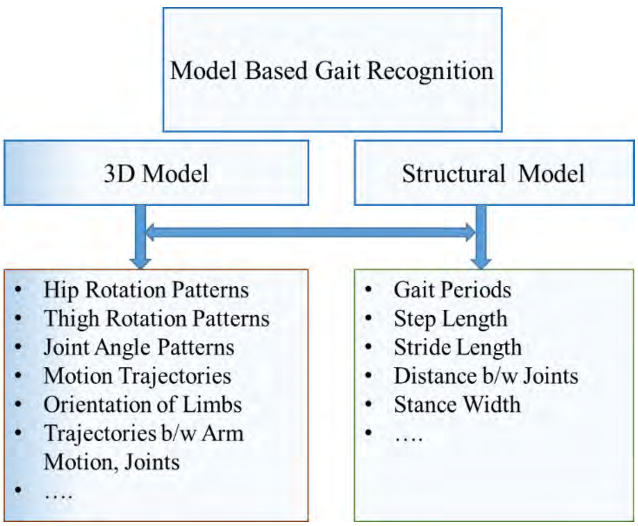

FIGURE 12. **Model based gait recognition approaches and possible features that can be used to represent a gait signature.**

model, 3D model) are fitted on walking sequences of each frame of gait cycle to obtain gait features [24] shown in Fig. 12. Model-based methods are easy to understand and are view-invariant, scale invariant and are not affected by background cluttering and noise. Because of these advantages, a model-based approach can be applicable for practical applications, because gait reference (query/probe) sequences and test (gallery) sequences are unlikely to be captured from the same viewpoint.

1) STRUCTURAL BASED GAIT RECOGNITION

The structural based gait recognition approaches estimate the geometrical and structural properties of individual subjects. The advantage of this method is that it is robust against lighting variations, segmentation imperfection, view variations, and background cluttering. This method extracts time-varying gait parameters, motion parameters of human gait shown in Fig. 12.

Based on the structural approach Abdelkader *et al.* [66] proposed a parametric method for identifying people in low-resolution videos based on height and stride parameters of an individual gait. They defined that performance was significantly enhanced by using height as an additional discriminant feature. They have extracted four view-invariant gait variables (parameters) from low-resolution videos, i.e., mean, amplitude of oscillation, cadence and stride length. The primary objective of their work was to depict that stride and height are discriminating features that can be used for personal identification. They theorized that if these features (stride and height) are combined with other biometric traits like face recognition (multimodal), high recognition accuracy can be achieved.

Activity-specific biometric means extracting an individual recognizing properties or of an individual's behavior that is appropriate only when a person is performing a specific action. Bobick and Johnson [67] proposed an approach for gait recognition based on activity-specific parameters. They define subjects walking action as an activity specific biometric and extract static body and stride parameters for recognition. A confusion metric based on mutual information has been used to estimate the effectiveness of the extracted parameters. For gait recognition, two set of gait features were generated. The first set consists of four distances namely (distance between head and foot, head and pelvis, foot and pelvis, left foot and right foot). The second feature set was the distance between (head and foot, foot and pelvis).

The second feature efficiently used in viewing variation conditions. The author also figures out that background subtraction of outdoor scenes is affected by shadows. Gaussian modelling approach has been used to remove shadow effect on outdoor gait sequences.

Many researchers have focused on recognition based on human walking and demonstrate promising results. The question arises whether analyzing leg motion, variations in speed or running are useful in recognizing a human. Running with a major biomechincal tranformations is an extension of walking. Running and walking of a human has unique bilateral symmetry characteristics [68]. Bilateral symmetry means when a person walks or runs there is an interchange in the direction of the left arm and right leg with the right arm and left leg and vice-versa. Features that distinguish walking from running are stride length and stride duration. Kinematic features of walking also differ from running because with an increase in velocity there is an increase in joints motion. To investigate how running and walking can be used for human recognition, Yam *et al.* [68] lay down a model-based automated approach for human recognition by walking and running. They have developed two models the bilateral symmetry model and the forced coupled oscillator model, which was based on the concept of pendulum motion. These models used for extraction of thigh and leg motion features simultaneously. The extracted features could be used for determining the relation between running and walking that could be used for human recognition. They defined that to extract thigh and lower leg features, the first hip model has to be created, which acquire hip motion. The study revealed that the vertical motion of the hip is an important characteristic which differs both from walking and running.

Fusion of shape and motion features for gait recognition has been proposed by Kim *et al.* [69]. They employed prediction based hierarchical active shape model(ASM) for gait cycle extraction, in which motion detection, object region detection, and active shape model features were extracted which lessen the problem of background extraction, shadow removal and improve the recognition rate. They employed a Kalman filter to predict global motion, which reduces the unpredictable factors in the shape and motion estimation process like illumination changes, shadows, and self-occlusion. Their proposed algorithm achieved 97% accuracy under view variation condition.

Identification in dynamic environments is a significant and challenging problem. In Deterministic learning (DL), the learning theory provides a systematic design approach for nonlinear system identification, dynamic pattern recognition and intelligent control for non-linear systems. Based on this idea Zeng *et al.* [70] proposed a model-based human recognition using deterministic learning. In this work, they considered sagittal plane for human gait recognition. Silhouette lower limb joint angle was considered as gait features for recognition. They employed a radial basis neural network through DL for achieving accurate identification.

a: MARKERLESS GAIT RECOGNITION

Vision-based human motion analysis systems are classified into three consecutive stages namely detection, tracking, and perception of their activity. In traditional model based gait recognition, the majority of methods proposed for motion analysis are marker based. An issue with the marker-based system is that reflective markers or sensors are attached at some crucial body joints of the human body to capture their motion. However, gait recognition as an application in automated surveillance monitoring system requires the markerless system to acquire body joints motion patterns for analysis.

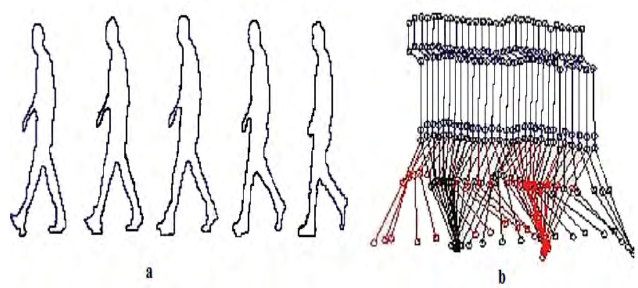

FIGURE 13. **2D stick figure extraction from human body silhouette from nine body points for each sequence [71], (a) depicts the body contour formation and (b) 2D stick figure formed based on nine body points.**

Yoo *et al.* [71] presented a back-propagation neural network for automated gait recognition. In this approach, nine body coordinates (body points) were extracted from the silhouette image of each sequence of individual subjects. Then, a 2D stick figure was extracted from these body points as shown in Fig. 13. Ten features were extracted from these figures and the back-propagation neural network was used for recognition. The overall accuracy achieved from their approach was 90% for thirty subject datasets.

In another work, Jang and Nixon [72] proposed an automated marker-less human gait recognition system in which gait motion was represented by a sequential set of planar 2D stick figures. Total eight planar 2D sticks were generated from body contour with six body joints. The sequence of gait figures was used for calculation of motion parameters and to characterize the human gait patterns. kNN classifier was used for classification based on motion and statistical features.

Wagg and Nixon [73] proposed a fully automated model-based approach for gait extraction based on hierarchical mean shape, motion information, and local adaptation. Anatomical data was used to generate shape models that are consistent with standard human body proportions. In the preprocessed approach, the Gaussian averaging filter used for noise removal and Sobel edge detection used for generation of edges of moving objects and temporal median of neighboring frames for background subtraction. They evaluated that majority of potential recognition parameters lie in static shape parameters and cadence. A complex parametric model reveals greater recognition potential in gait dynamics.

Bouchrika and Boukrouche [74] proposed a marker-less extraction of gait features, which are used for individual recognition. Gait features extracted using Haar-like template under view variation condition. In this marker-less model, an angular model template that describes the human motion has been employed for the extraction process. Gait features consist of the lower legs angular rotation measurement and spatial displacement of the human body. Gait features are localized by Haar-like template because the performance of object detection and recognition in a real-time system is robust and fast. To remove the irrelevant and redundant feature's Adaptive sequential forward floating selection (ASFFS) method has been employed. The posture of legs has been estimated based on a frame by frame basis and for each person angle between hip and knee are extracted from six viewpoints.

Elliptical Fourier descriptor based automated marker less extraction of gait features for human identification based on body joints proposed by Bouchrika [75]. Based on these body joints gait features including an angular measurement of the legs as well as the spatial displacement of the body trunk has been extracted. To derive parameters from the elliptic descriptor, recursive evidence gathering algorithm has been employed under scale and rotation transformation. ASFFS search algorithm has been used for feature subset selection to achieve better classification rate.

Another approach has been proposed for marker-less gait analysis and recognition by Bouchrika and Nixon [76], in which an Elliptic Fourier descriptor modeled human gait motion for tracking and feature extraction. They fused static and dynamic features for recognition. Static features are body height, stride, and height of different body parts while dynamic features include the phase-weighted magnitude of the Fourier frequencies for the hip and knee angular motions.

b: ARMS FEATURE FOR GAIT RECOGNITION

In recent researches, hand motion has not been considered as a feature vector for recognition. The reason behind is due to carrying objects by subject or because of the disorder due to bust. To study and verify the importance of arm motion for recognition, Tafazzoli and Safabakhsh [77] proposed a model-based method for gait recognition based on the leg and arm movement. To create a model based on the movement of body parts, they employed active contour and Hough transform using anatomical facts. They initially segment the human body into three regions. The size of each region was computed as a percentage of body height. Motion information of the person was extracted through velocity filtering algorithm, which was used to describe a person's accumulated average shape over gait frames. Ellipses were framed for head and torso, and two pairs of the line segment for each leg has been used to estimate the shape and size of segmented regions as shown in Fig. 14. To analyze the efficiency of the proposed approach combined feature sets were employed, that is static features (mean shape model) and dynamic features (movement of joint positions of leg and arms) which achieves an accuracy of 94.5%. Gaussian noise was removed from frames with adaptive kernel regression.

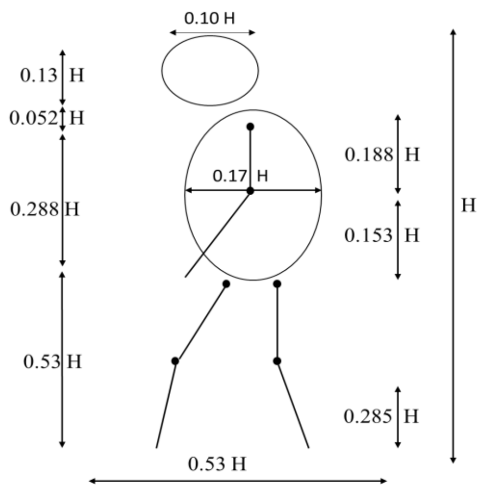

FIGURE 14. Region segmentation and ellipse formation on head and torso [77].

2) 3D MODEL-BASED GAIT RECOGNITION

The objective of gait recognition is to identify the discriminative features that differentiate people according to their style of walking. The current research approaches are based on 2D gait video sequences. Limitation arises in 2D gait recognition because of the fixed camera viewpoint, self-occlusion, and surface variations that will effect to attain correct and accurate results.

To handle the drawback of 2D images, 3D gait recognition is captured simultaneously by more than two static calibrated cameras. 3D gait recognition helps to overcome fixed viewpoint difficulty, self-occlusion, and surface variations to obtain motion sequences as applicable in a real-world scenario. In 3D recognition, a person's gait is tracked with the help of 3D human models, which helps in the reconstruction of 3D human structure and extraction of dynamic features to perform human recognition.

To tackle the problem of 2D recognition, Gu *et al.* [78] have proposed an approach based on 3D human joints. They worked on action and gait recognition based on 3D human joints. In this research, a marker-less pose recovery approach has been employed for the automatic extraction of 3D human joints for action and gait recognition. Two types of features were recovered, i.e., movement features and configuration features. Movement features represent the global motion of the subjects, including a change in body position, orientation, and height of the body. Human body joint sequences which depict the changes of configuration of human body segments are termed as configuration features. They used movement features for action recognition, and configuration features for gait recognition. The configuration features consist of normalized human joint sequence vectors. They also considered lower limb features, which are more robust gait features for recognition. Maximum a posteriori (MAP) classifier was used for gait classification based on two feature vectors (first, normalized body joint sequences of the whole body and second, normalized joint sequences of two legs).

Zhao *et al*. [79] proposed an approach based on 3D gait recognition. In this work 3D human model is created on video sequences taken from multiple cameras. Two feature sets are generated, static feature set including the length of key segments, and a dynamic feature set including motion trajectories of lower limb for recognition. They achieved the accuracy of 70% while combing both static and dynamic feature sets and claimed that the proposed method deal robustly with the effects of view and surface variations.

Krezeszowski *et al*. [80] outlined a markerless 3D motion tracking approach proposed for view- independent person identification. Particle swarm optimization algorithm was employed for motion tracking. MoCap ground truth data were used to evaluate motion tracking method. Four calibrated and synchronized cameras were employed to acquire 3D motion from video sequences, and a dataset of 20 subjects was created. In this dataset, each subject performed two straight walking and two diagonally. The tensorial gait data was extracted for classification, which was optimized (dimensionality reduction) by Multilinear Principal Component Analysis (MPCA) algorithm. Navie Bayes and Multilayer Perceptron (MLP) classifier were employed for identification. By analyzing the results, it is concluded that MLP achieves 90% of accuracy (Rank 1) as compared to the Navie Bayes classifier.

In another work, to handle the view-independent issue, Kwolek *et al*. [81] proposed a 3D marker-less motion tracking algorithm which acquires motion data for human gait identification. To analyze the accuracy of 3D motion tracking, ground truth data was generated based on marker-based motion capture system. Ground truth data was generated by thirty-nine reflective markers attached to the body joints. They created a dataset of 22 subjects to evaluate the marker-less motion tracking system. Three classifiers were employed, Navie Bayes, Multilayer Perceptron (MLP) and Support Vector Machine (SVM). Support vector machine classifier achieved a promising accuracy rate of 93.5% for rank 1 and 99.6% for rank 3 as compared to two other classifiers.

To tackle view angle variation problem of 2D video based gait recognition, Wang *et al*. [83] used second-generation Kinect V2 tool to create 3D skeleton based gait database. This dataset has both 3D information of joints and corresponding 2D silhouette images. Static and dynamic features were extracted for recognition of the person.

Static features include a relative length of the skeleton joints while dynamic features have an angle between skeleton. There dataset consists of 52 subjects with 6 view directions (0, 90, 135, 180, 225 and 270°). It is concluded that fusion of static and dynamic features, increases classification rate above 90% under different view variation conditions.

Urtasum and Fua [82] designed a 3D temporal motion model for gait analysis which was robust to occlusions, clothing, illumination changes, and independent to view variations. To track a motion model they have used data points which define the model. They have taken samples of four-persons using optical motion capture system. Each person is walking at 9 different speed variations on treadmill ranging from 3 km/h to 7 km/h with an increment of 0.5 km/h.

B. MODEL–FREE (HOLISTIC OR APPEARANCE-BASED) APPROACHES

This section describes the work done for gait recognition using model-free approaches. In this method, no prior geometric model of the human body is formed but focuses on either shape or motion characteristics of human body silhouettes.

Features in the model-free approach are directly extracted from the binary part of gait contour, which is insensitive to the color and texture. The computational cost of model-free gait representation is low as a comparison to model-based representation. Even quality of silhouette does not effect on gait recognition performance. Being an effective method for gait recognition, this method usually not robust to view variations, appearance changes (such as clothing, carrying conditions, and shoe type) and scale.

The model-free approach considers three methods (Spatiotemporal motion-based method, statistical method, and Physical parameter method) for identifying the unique gait features for recognition as shown in Fig. 15.

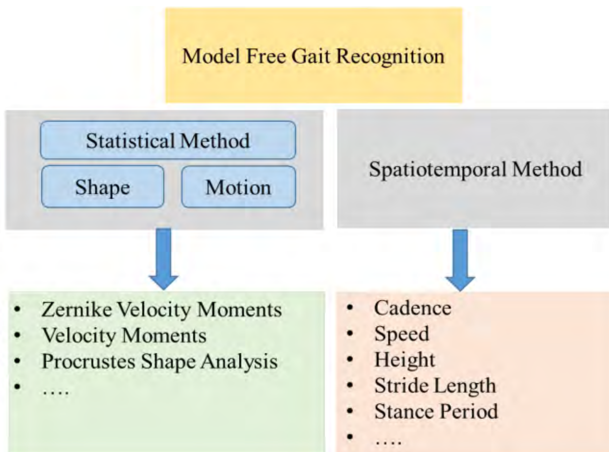

FIGURE 15. Model-free approaches and their corresponding features.

1) SPATIOTEMPORAL METHOD

Spatiotemporal method manages both space and time information in video sequences. The major benefit is that it is easy to implement with low computational complexity.

a: TEMPORAL TEMPLATE APPROACH

Temporal template approach works by comparing and matching features between the probe input patterns and the gallery stored patterns; i.e., a spatial comparison is performed temporally, on a frame-by-frame basis. These approaches directly compare the probe image sequences with the gallery sequences.

Sundaresan *et al.* [91] have proposed a temporal based approach, i.e., a temporal template matching framework based on a hidden Markov model (HMM). Due to the statistical nature of HMM, it provides robustness and flexibility to the framework for selection of feature vectors. Their framework assumes that during gait, individual subject transitions between different discrete postures do not become dependent on the particular feature vector. For feature vector estimation they employed binarized background subtracted image and used three distance matrices (Euclidean distance, Inner product (IP) distance and the sum of absolute difference (SAD) distance). They worked on three covariates conditions (walking surface, shoe type, and view variations).

In another work based on temporal characteristics, Sarkar *et al*. [48] proposed a baseline algorithm which used the temporal correlation of silhouette for recognition. The motive of work was to develop a method against which future performance would be evaluated. They proposed a semiautomatic approach of a bounding box which was used to match silhouette frames. Gait sequences were partitioned by estimating gait period, which was used for temporal classification. They created a database, which examines the effect of five covariates on performance, i.e., view angle variations, change in shoe type, variation in walking surface, carrying or without carrying a briefcase and elapsed time between sequences being compared. It is concluded that time has the most significant impact on recognition rate.

b: SPATIOTEMPORAL APPROACHES

The challenging issue with temporal template approach is that it is based on comparing images on a frame by frame basis. The efficient approach is to use accumulated motion features. In the spatiotemporal approach, the spatial structural (appearance) and temporal transitional (dynamics) features of gait are captured. The key advantage of this method is low computational complexity and the reduced feature vector, which ease in implementation. However, this method is prone to variations in camera orientation and appearance change (walking speed, clothing variations, and carrying conditions).

In a novel approach to extract motion information from cluttered video image sequences proposed by Havasi *et al.* [92], which is based on spatiotemporal input information to detect and classify patterns of human movement. They employed symmetry features for detection and tracking of a pedestrian in a real-time scenario. They used modified kernel based (non-linear) Fisher discriminant analysis (KFDA) for classification. Their proposed method was suitable for detection of subjects in multi-person images.

Another novel approach for gait recognition using linear time normalized proposed by Boulgouris *et al.* [93]. They transformed extracted silhouette frames into a low-dimensional feature vector to estimate distance and angular features from the center of the silhouette. They evaluate their approach on seven probe conditions.

To present the application of spatiotemporal features for human gait recognition in surveillance Ran *et al.* [94] proposed an approach in which video sequences were decomposed into x-t slices. These decomposed sequences generate periodic patterns which were referred to as double helical signatures (DHSs). They employed an iterative local curve embedding algorithm for extracting DHS from gait video sequences. The objective of DHS is that it revealed the geometric symmetries by encoding the appearance and kinematics of human motion and is helpful in detecting simple events in human gait and extracting parameters. The signature integrates temporal body kinematics with shape, motion, and appearance. Another advantage of DHS is that it has effective learning in the presence of imperfect gait period, self-occlusion and clutter.

Appearance-based gait analysis methods require foreground and background subtraction in pre-processing, which causes additional time complexity and also affect the performance due to imperfect background-foreground subtraction. Appearance-based approaches are also adversely affected by clothing variations and carrying variations. To handle these issues Kusakunniran *et al*. [32] proposed an approach to extract gait features directly from raw videos. In this approach, space-time interest points (STIP) are detected in the spatiotemporal domain. Concatenation of Histogram of oriented gradients (HOG) and a histogram of optical flow (HOF) is used as STIP descriptor.

Abdelkader *et al.* [101] proposed a gait model to extract the stride length and cadence of a person gait for automatic identification and verification. Their approach works better with low-resolution videos. Non-parametric background modelling technique was used for extraction of the foreground object, and two features were extracted, i.e., cadence and step length. Bounding box width has been used to extract the human gait cycle. Bayesian decision approach has been used for classification. The method was robust to different factors such as lighting, clothing and tracing errors and stride length. Cadence parameters are principally efficient for classification under view variation.

c: ENHANCED SPATIOTEMPORAL APPROACHES

In traditional spatiotemporal approaches, gait is considered as a sequence of templates, which consumed massive storage space and computational time complexity for evaluation is high. To overcome this issue Man and Bhanu [31] proposed a new spatiotemporal gait representation, which is termed as Gait Energy Image (GEI). In GEI motion information is represented in a single image by preserving the temporal information.

The GEI is defined as

$$G(i, j) = \frac{1}{N}\sum_{t=1}^{N} I(i, j, t) \tag{12}$$

Where N defines the number of silhouette frames in the gait cycle, t represents the frame number in a gait cycle at a moment of time and $I(i,j)$ is the original silhouette image with (i,j) values in the 2D image coordinate. A sample GEI is shown in Fig.16.The GEI templates are beneficial for space storage and computational time. GEI templates are less sensitive to noise.

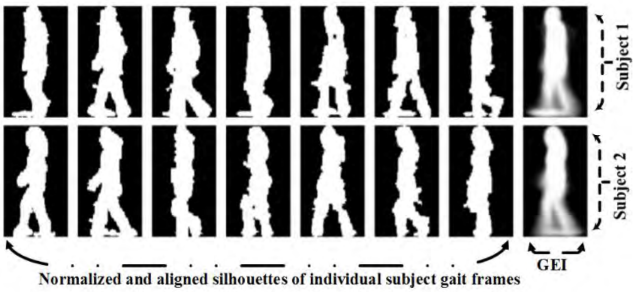

FIGURE 16. **Gait Energy Image (GEI) from silhouettes of each subject gait frames, taken from [31].**

Rida *et al.* [95] proposed a gait recognition approach using a modified phase–only correlation approach based on GEI representation. This framework applied supervised feature extraction method, which was able to select relevant discriminative features for human recognition under clothing, carrying and intraclass covariates. They employed band-pass-type spectral weighting function to improve the phase-only correlation (POC) method to enhance the recognition performance. This is an efficient and effective approach to match images with low texture features.

In another work Rida *et al.* [96] applied the group lasso to segment GEI to select discriminative human body parts which reduce intra class variations. GEI prove to be an efficient gait silhouette template for human recognition. However, GEI loses information in a gait sequence which affects performance due to changes caused by covariate conditions such as clothing, carrying conditions and view variations. Static shape information of human gait silhouette proved to be an important feature for silhouette-based gait recognition [132].

Due to these issues in GEI, Sarkar *et al.* [48] proposed a novel gait feature representation approach termed as Gait Entropy Image (GEnI). Shannon Entropy method has been used on gait silhouettes to distinguish between a static and dynamic portion of GEI. Entropy over the complete gait cycle represented as

$$I(i,j) = \sum_{k=1}^{k} P_k \log_2 P_k(i,j) \tag{13}$$

Here (i, j) are pixel coordinates and $P_k(i,j)$ is the probability of pixel (i, j). GEnI obtained by scaling and discretizing I (i, j)

$$\mathrm{GEnI(i,j)} = \frac{I(i,j) - \min(I(i,j)) \times 255}{\max(I(i,j)) - \min(I(i,j))} \tag{14}$$

In another variant of GEI, to preserve the temporal information from loss, Wang *et al.* [98] proposed a method known as Chrono-Gait Image (CGI), which is based on multi-channel temporal encoding scheme. In CGI, the contour image of the gait frame was encoded with multi-channel mapping function within the same gait sequence to generate single CGI. A sample of CGI temporal templates shown in Fig.17.

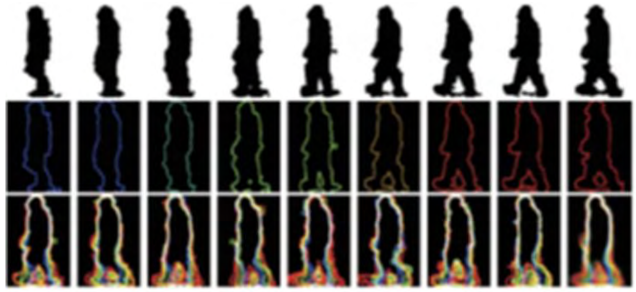

FIGURE 17. **An example of CGI templates taken from Wang *et al.* [98]. The first row shows silhouette frames of the subject, the second row depicts the multi-channel contour image, and the last row defines generated CGI templates of a gait period.**

The Chrono-Gait Image (CGI) [98] is defined as

$$\mathrm{CGI(i,j)} = \frac{1}{\mathrm{N}} \sum_{\mathrm{k}=1}^{\mathrm{N}} P_k(i,j) \tag{15}$$

$$P_{\mathrm{k}}(\mathrm{i,j}) = \sum_{t=1}^{n_i} C_t(i,j) \tag{16}$$

Where N is the number of frames in the 1/4 gait periods and P_{k} (i, j) represents the sum of total n_i multichannel contour images $C_t(i,j)$ in 1/4 gait period.

2) STATISTICAL FEATURE METHOD

In gait recognition, silhouette statistical features usually describe the shape and motion patterns. Procrustes shape analysis [35], [99], [130] and Elliptic Fourier descriptors [130] are most used approaches to describe the shape features of a gait silhouette. Velocity moments [139], Zernike velocity moments [131], etc. can be used to describe silhouette motion features. Statistical methods are more robust to noise. In gait recognition, shape provides greater discriminative information than its kinematics.

Based on this theory, Wang *et al.* [99] proposed statistical shape analysis approach for human identification. They employed Least Median of Squares (LMedS) method for background subtraction and gait signature obtained by using Procrustes shape analysis approach. Three viewing angles 0°, 45°, 90° were evaluated using classifiers NN, kNN and ENN. They have been able to achieve better recognition rate above 85% for three view angles. Wang *et al.* [100] proposed another approach based on silhouette shapes for recognition. Their method was based on statistical principal component analysis (PCA) method. Background subtraction was performed to extract spatial silhouettes shapes, and the eigenspace transformation applied to extract features. They apply spatiotemporal correlation (STC) and normalized Euclidean distance (NED) similarity measures with the nearest neighbor classifier for evaluation.

The appearance of an individual change with variation in different clothing, which results in a problem for gait recognition. To handle this situation Nandy *et al.* [97] proposed a statistical shape analysis method based on GEI.

They segmented the GEI of an individual subject and extracted GEI edge contour features.

In [99] Wang *et al.* proposed a statistical (appearance) features of gait for recognition which are static. Combining static and dynamic features of human gait for recognition proposed by Wang *et al.* [36]. In this work, Procrustes shape analysis used for extracting static information of the human body and dynamic features were extracted from trajectories of lower limb joint angles. The framework is a combination of model-based and appearance based methods. ENN used for evaluation of static features and dynamic features. Similarity measurement between two gaits was based on distance measures, i.e., smaller the distance more similar the gaits. They achieved the correct classification rate of approximately above 90% for individual features and fusion of features.

A wok on sequences based object analysis and description was done by Shutler and Nixon [131]. In this work statistical shape and motion in image sequences are described by zernike velocity moments. The reason for employing Zernike moments is that due to the non-orthogonal nature of Cartesian velocity moments, Zernike moments have less correlation description even in large databases. This less correlated description improves performance under noise as compared to Cartesian velocity moments. Two image sets were generated to apply velocity moments, i.e., first was a binary silhouette or spatial templates (ST), which gives shape information while optical flow images or temporal templates (TT) provide motion information. They employed kNN classier and leave-one-out rule for evaluation.

A baseline algorithm proposed by Collins *et al.* [102], in which human identification was based on body shape and gait. The method was based on matching 2D silhouette images extracted from keyframes across gait sequences. The approach was robust against noisy video data and not affected by clothing color and texture. However, the method as sensitive to view variations because of matching 2D shape silhouettes.

VI. APPLICATIONS OF GAIT RECOGNITION

In this section, we outline the possible applications of gait recognition. We consider two important applications areas: soft biometric and clinical analysis. The soft biometric area covers applications of gait recognition in gender recognition and age estimation. The second application area is concerned with the detailed analysis of the gait motion data, which may be used in the clinical analysis of, e.g., orthopedic patient diagnosis, Parkinson patient diagnosis.

A. SOFT BIOMETRIC

Application of gait as a gender recognition improves a computers perception capability and is useful in many applications such as intellectual and visual surveillance which track moving objects, classify them into different classes. Gait based gender classification is used to divide the tracked object into two categories: male and female, which can improve search speed and efficiency of retrieval of a suspect in a vast video database. In customer statistics, gender classification helps the manager to know more about their customer interest and provide better service to them.

Average gait image for gender recognition has been proposed by Li *et al.* [41]. They had segmented human gait silhouette into seven components (such as head, arm, trunk, thigh, front-leg, back-leg, and feet). The analysis was done on motions of different parts of a human silhouette. They had analyzed that head, back-leg and feet are not useful for gender recognition. Regarding the walking surface or the carrying of a briefcase, arm, and thigh component reduce the gender recognition. They used SVM for classification.

To overcome the drawbacks of current approaches for collecting gait sequences with unrealistic assumptions such as a person walk in a fixed direction or a predefined path, J Lu *et al.* [103] proposed an approach based on arbitrary walking directions gait sequences, to investigate human identity and gender recognition. The first extracted human gait silhouette images by background subtraction and clustered them. They considered a cluster based averaged gait image as features set. To minimize intra-class sparse reconstruction error and maximize inter-class sparse reconstruction error, they propose a sparse reconstruction based learning method, to learn a distance metric, so that discriminative information can be used for recognition. Sudha and and Bhavani [104] presented a spatiotemporal approach for gender classification. They had extracted five binary moment features and four anatomical features from the human silhouette. To evaluate the performance they applied probabilistic neural network (PNN) and support vector machine (SVM) on the CAISA-B dataset. Supervised modelling approach proposed by Hu *et al.* [42], where shape and temporal dynamics of both genders are integrated into a sequential model termed as a mixed conditional random field (MCRF), which provides various spatiotemporal features. They had segmented the silhouette image into a grid of 2x2 and 4x4 and depicted that combining these grids is sufficient for gait shape representation. Cross race-based gender classification has been proposed by Yu *et al.* [105].

They combined human knowledge to analyze which body component provides better gender classification rate. They used gait energy image as gait feature and segmented it into five components: head and hair, chest, back, waist and buttocks and legs. The support vector machine has been used to evaluate the potential of gait-based gender classification.

Fusion of multiview for gender classification proposed by De [106] and tensor data has been extracted from GEI for recognition. To reduce dimensionality multi-linear principal component analysis (MPCA) has been employed. Pose based gender recognition based on gait depth image captured through Microsoft Kinect has been proposed by Kastaniotis *et al.* [60]. Gait motion features were extracted using an angular representation. They created a new dataset using Microsoft Kinect, consisting of 5 sequences performed by 30 volunteers.

To overcome the problem of some open visual surveillance systems such as airports, railway stations and building entrances where it is difficult to collect gait samples in advance for identification purpose. Under such circumstances, recognizing another biometric attribute such as gait based age information estimation of concern person may also prove to be useful and desirable. Lu and Tan [43] presented a new approach for human age estimation based on gait features. To well characterize and correlate the age and gender information for age prediction, the said approach learns a multi label-guided subspace. They extracted Gabor magnitude and Gabor phase information from gait sequences and performed multiple feature fusion to enhance the age estimation performance. GEI has been used for feature extraction because of its robustness and effectiveness. Hidden Markov Model (HMM) based age estimation proposed by Zhang *et al.* [128], in which they consider shape variations among subject on the basis of contour.To reduce the dimensionality, Frame to Exemplar Distance (FED) has been employed, and HMM was trained on FED feature vector and achieved correct classification rate of 80%.

B. CLINICAL ANALYSIS

In recent years human gait analysis plays a vital role in video surveillance for security, and identification. Quantitative measurement of gait patterns, e.g., cadence, gait speed, and step length, provide valuable information on the development of aging and disease diagnosis.

Weiss *et al.* [107] analyzed kinematic and kinetic gait changes in rheumatoid arthritis (RA) patients in comparison with healthy individuals. They examine levels of functional disabilities of gait parameters. They proposed a 3D motion model to analyse the kinematic and kinetic features of arthritis patients and healthy persons. Their study revealed that RA patient's lower limbs have decreased in kinematic and kinetic gait parameters as compared to healthy individuals.

Gait analysis also proved to give promising results in Parkinson disease detection. Saad *et al.* [108] proposed an approach to detect freezing of gait (FOG) in Parkinson's disease patients; which is due to sudden failure of the walk. For the data acquisition to detect FOG, they used the multi-sensor device. The acquired signals were analyzed to extract time and frequency domain features, and principal component analysis has been used to select optimal features that efficiently represent the freezing of gait features. The combined Gaussian neural network technique has been used in the freezing of gait (FOG) for classification. The benefit of using the combined Gaussian neural network (GNN) is that it has fast learning capability to obtain high accuracy with fewer weights and reflects the complexity of the data to separate into different classes.

Human-machine communication and computer intelligence are swiftly developing into interdisciplinary areas. Human gait analysis for Parkinson's disease detection can be accomplished by specialized cameras with specific sensors which detect movement with high precision. Ťupa *et al.* [109] have proposed an approach for the detection of gait disorder which is due to Parkinson disease. They employed Kinect sensors to extract individual subjects gait disorder data. The motive of using the Kinect sensor is that it is much less expensive and has sufficient accuracy for many applications. The RGB camera in MS Kinect records video image frames with a frequency of 30fps (frames per second). Information stored by both RGB camera and depth sensor is of 640x480 resolution. They used a neural network to evaluate the efficiency of the proposed approach.

VII. GAIT RECOGNITION RESEARCH CHALLENGES

Physiological or behavioral characteristics of an individual person prove to be an efficient resource for automatic identification or verification for surveillance and security applications. Many biometric traits like fingerprint, face, and iris, have proven great importance for human identification or verification, but these traits suffer due to their obtrusive, and perceivable nature. Biometric gait is one of the most popular behavioral traits and has advantages over other physiological traits (such as the face, DNA, and iris.) due to unobtrusive, non-invasive and non-perceivable nature, which makes it a robust biometric trait for human identification or verification.

Some factors which affect the effectiveness of gait like carrying conditions, viewpoint variations, walking surface, clothing conditions, elapsed time, footwear, physical conditions (such as pregnancy, leg or foot injuries), even drunkenness can change walking patterns of a person. These factors classified into three categories as shown in Fig.18. Among the covariates as above, one of the crucial challenges that frequently occurs in gait recognition is occlusion, especially in real-world surveillance and control access. Occlusion can occur because of multiple factors (person crossing the probe gait leads to hiding its gait patterns, or two or more person walking in a group). The affect of covariates mentioned above is investigated for single gait recognition (person walking alone under different covariates).A recent study on persons walking in a group (two or more) termed as multi-gait, has been investigated by Chen *et al.* [90].

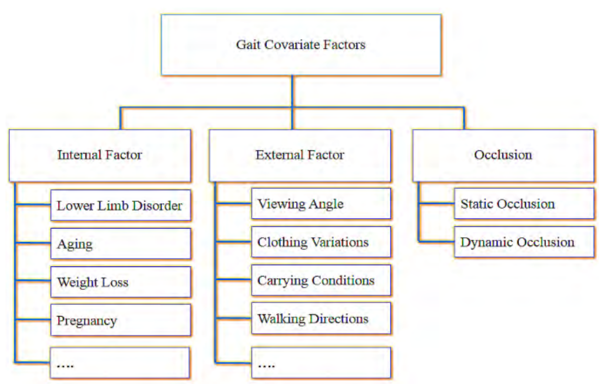

FIGURE 18. Covariate factors are affecting the performance of a gait recognition system.

In this section, we have analyzed covariate factors, External factors (view variations, appearance changes due to clothing and carrying conditions) and occlusion factors (Static and Dynamic) that affect gait performance and investigate what measures have been taken to what extent to overcome these issues.

A. GAIT OCCLUSION

Generally, in gait recognition, we require full gait cycle, but in case of occlusion, we are unable to acquire complete gait cycle (for example, a person walking in front of the probe gait or, one or more subjects walking with each other), shown in Fig.19. So it becomes a challenging issue to extract a complete gait cycle. Gait occlusion is classified into two classes [61]: 1) static occlusion and 2) dynamic occlusion.

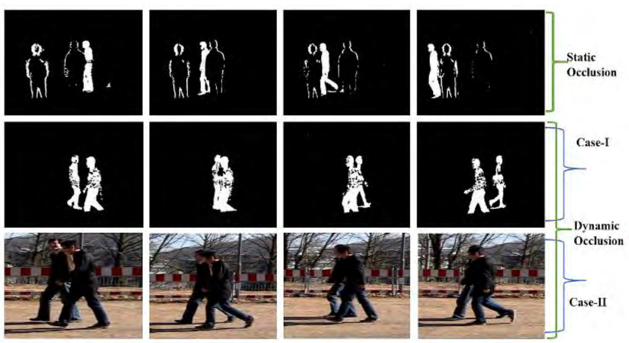

FIGURE 19. Different classification of occlusion. First and second row samples are taken from dataset created by [61] and last row samples taken from MPII-2 person dataset [133]. First rows show static occlusion, in which white silhouette object is walking in front of two standing objects. Second and third row defines two cases of dynamic occlusion. Case-I, in which two persons cross each other during walking and Case-II, in which two persons are walking side by side.

1) Static occlusion, probe gait is occluded by standing people or by some other static obstacles (like beams, pillar, living or non-living objects).
2) Dynamic occlusion is divided into two cases. In the first case when one or more walker cross the probe subject and occlude their gait and in the second case, when two or more person walks together, this is also termed as multi gait.

Hofmann *et al.* [61] proposed a novel dataset for gait recognition to handle static and dynamic inter-subject occlusion problem. They proposed two baseline algorithms based on the color histogram and GEI. They have estimated that color histogram information is more variant to change in clothing while GEI is an efficient gait recognition method because it captures temporal motion information based on gait cycle, which is invariant to appearance-based features. Based on [61] dataset, Roy *et al.* [110] proposed a novel approach for gait recognition in the presence of occlusion. In their approach, they detect the occluded silhouettes frames and then reconstruct them using Balanced Gaussian Process

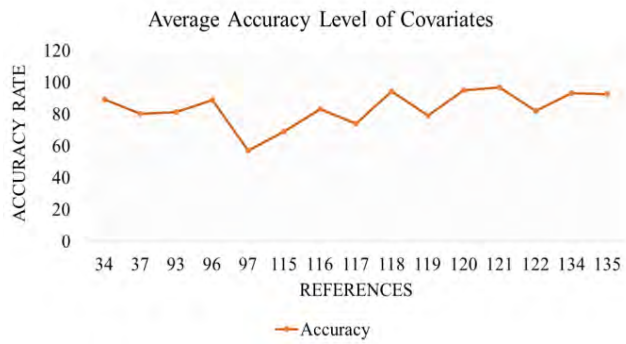

FIGURE 20. Shows the average accuracy rate of covariates (view and appearance change).

Dynamic Model (BGPDM). They achieved the reconstruction accuracy of 90%.

Multi-individuals walking together is another factor which affects the gait pattern and is termed as multi gait. Multi gait is the motion which is composed of at least two persons walking together, have the same walking speed and not separated temporally. Multi gait recognition is helpful in intelligent video monitoring systems because if multi-gait cannot be recognized accurately, then it gives an immense advantage to criminals to escape easily by walking along with other people when gait monitoring system monitors them.

Participant segmentation in multi-gait recognition is a challenging aspect. Chen *et al.* [90] proposed an approach for multi gait recognition, in which the hypergraph partition was proposed for human segmentation. After segmentation of each participant, multi-linear canonical correlation analysis algorithm (UMCCA) was used for recognition of each participant. Hypergraph partition was employed after using human detection and tracking technology for achieving better segmentation of participants. Hypergraph-based segmentation proved promising results because it can describe the details of the small pixel area of human body parts. In a recent study, superpixels proved to be an efficient approach for object segmentation under occlusion scenario. Based on this Chen *et al.* [111], proposed superpixels based human graphlets for accurately tracking and detection of multi-objects (participants in multi gait). Superpixels based graphlet creation was based on two approaches: simple linear iterative clustering (SLIC) which is faster in computation and is memory efficient and Region Adjacency Graph (RAG). Conditional Random Field (CRF) was employed to estimate the latent variables. After segmentation of the subject, dynamic features were extracted based on dense trajectories due to its efficiency. In another work, Chen *et al.* [112] used hierarchical association for participant tracking and solving the Maximum a Posterior problem using the Hungarian algorithm. Edgelet features were used to detect participant body parts and static and dynamic characteristics were used for better gait classification. To minimize the effect of occlusion

TABLE 7. Outline work done in gait recognition under view variation, appearance change conditions.

S. No.	Reference /year	Methodology	Covariate condition
1	Muramatsu et al. [114],2015	Proposed arbitrary view transformation model (AVTM) that compares gait trait pairs from an arbitrary view. Proposed model eliminated the discrete of view transformation model (VTM) and improved the accuracy of RankSVM.	View variation (Cross view)
2	Rida et al. [95],2015	Proposed a supervised, modified phase-only correlation (MPOC) for selecting discriminative features to enhance gait recognition under different covariates.	View variation + Appearance change (Clothing + Carrying)
3	Jia et al. [30],2015	Proposed a novel view-invariant gait recognition approach, based on gait silhouette contours analysis and view estimation. Gait flow image is extracted by the Lucas-Kanade method,andProcrustes shape analysis (PSA) has been employed to estimate the mean shape of head and shoulder.	View variation
4	Arora et al. [115],2015	Proposed a Gait Information Image(GII) based on information set theory and extract two gait features that are Gait Information Image with Energy Features (GII-EF) and Gait Information Image with Sigmoid feature (GII-SF).	Appearance Change (Clothing + Carrying) + Speed variation
5	Choudhury et al. [116],2015	They proposed a two-phase view-invariant multiscale gait recognition approach (VI-MGR). This approach is also effective to variation in clothing and carrying condition. In first phase entropy of limb portion of gait energy image is employed with VI-MGR for gait matching and in second phase gait matching is done using multiscale shape analysis.	View variation + Appearance change (Clothing + Carrying)
6	Nandy et al. [97],2016	Proposed a novel statistical shape features from GEI edge contour to mitigate the effect of cloth variation in appearance change	Appearance Change (Clothing)
7	Rida et al. [96],2016	Body part selection based on motion and group lasso to select discriminative parts which are robust to the intraclass variations	View variation + Appearance change (Clothing + Carrying)
8	Zeng et al. [117], 2016	Deterministic learning theory employed to eliminate the effect of view variations for efficient gait recognition. Spatiotemporal features of eachsubject extracted to represent gait motion.	View variation
9	Wu et al. [118],2016	Proposed a deep convolutional neural network to identify the most discriminative gait pattern changes which help for identification human.	View variation (cross view + cross walking)
10	Choudhury et al. [119], 2016	Proposed an average gait key-phase image(AGKI) based on five key phases on gait image sequences to mitigate unpredictable variations in appearance change	Appearance Change (Clothing + Carrying)
11	Li et al. [34],2017	Proposed a video sensor-based gait representation, which employed deep convolutional features and joint Bayesian to model view variance.	View variation
12	Ebenezer et al. [120],2017	Genetic algorithm based automatic template segmentation to extract boundary for gait recognition. The proposed approach tested on Gait energy image, gait entropy image,and active energy image templates.	View variation + Appearance change (Clothing + Carrying)
13	Tanmay et al. [121],2017	Perceptual Hash algorithm(PHash) values havebeen computed over leg region of the Gait Energy Image to identifies the view variations and compares PHash values of different subjects view variations stored in the database	View variation + Appearance change (Clothing + Carrying)
14	Lishani et al. [37],2017	Vertically or horizontally GEI is segmented into equal regions to extract Haralick features for robust gait recognition under appearance change	Appearance Change (Clothing + Carrying)
15	Chaurasia et al. [122],2017	Proposed a novel algorithm for dynamic and static feature extraction based on Discrete Fourier Transform (DFT) and Random Walk (RW) representation.	Appearance Change (Clothing + Carrying)
16	Sharma et al. [134],2018	Proposed a new gait feature representation approach based on information set theory, derived from fuzzy set theory. Bipolar sigmoid feature generated from gait information image (GII), termed as GII-BPSF.	View variations + Appearance Change (Clothing + Carrying)
17	Sun et al. [135],2018	Proposed a model based approach for gait recognition using Kinect v2 sensor to tackle view variation problem. 21 body joints captured form 3D skeleton.	View variations

and to recover the occluded area accurately, they employed an occupancy map method. They used tensor analysis to preserve relationship and structure information of subjects in a multigait dataset. Tensor analysis has good capability to describe high dimension features.

B. VIEW AND APPEARANCE CHANGES

Among various gait challenges, two most challenging problems need to be addressed namely: (1) view angle variations and (2) subject's appearance change that occurs due to clothing variations and carrying conditions. Gait recognition

TABLE 8. Year wise summary of future work proposed from 2015 to as on July 2018.

S. No.	Reference / Year	Future Scope
1	Tafazzoli et al. [33] / 2015	Propose to generalize the genetic feature selection method on other view angle variations and outdoor data.
2	Rida et al. [95] / 2016	Their proposed method is sensitive to view angle variations and proposed to have robust view variation approach based on pose estimation technique.
3	Rida et al. [123] / 2015	Propose to investigate the proposed feature selection mask on view angle variation between training and testing data and extend their analysis on more datasets.
4	Arora et al. [115] /2015	In future, their proposed approach can be investigated under view variation condition.
5	Li et al. [34] / 2017	Propose to evaluate their approach to other covariates, i.e., appearance change (clothing, carrying conditions) and more view angle variations.
6	Choudhury et al. [116] / 2015	Propose to increase the view-invariant feature that can help to improve identification rate in the absence of matching probe view in the gallery and enhance feature subsets selection in order to capture most inter-subject discriminatory features that improve recognition under covariate factors.
7	Nandy et al. [97] / 2016	Their proposed approach is sensitive to speed variation and dependent on view angle. In future, they propose to extend their proposed approach to speed variations and employ Eigenspace transformation approaches to reduce the dimension of feature space.
8	Nandy et al. [124] /2017	In future to increase training subjects with significant variations in clothing conditions and also include feature analysis in the frequency domain.
9	Bouchrika et al. [75] / 2015	Aim to investigate the scalability issue of gait recognition and how it performs via increasing the number of subjects in the dataset
10	Kastaniotis et al. [86] / 2015	Propose to investigate their approach to investigating abnormalities in walking, falling prediction and mental state assessment based on gait.
11	Lishani et al. [37] / 2017	In future investigate the performance of the proposed method under other covariate factors such as walking surface and also study other features capable of improving the performance of our proposed approach.
12	Tanmay et al. [121] /2017	In future to explore more complex classier to improve gait recognition and explore features that are invariant to appearance change
13	Chaurasia et al. [122] / 2017	Future work to incorporate varying speed information in their proposed work
14	Sun et al. [135] / 2018	Focus to employ adaptive scheme to improve the recognition. Joint estimation through other devices will improve its generalization.

under view angle variations has been classified into three states [113]:

- Fixed view angle gait recognition, in which both probe and gallery gait are captured from the same view angle.
- Cross view angle gait recognition, in which probe and gallery gait are captured from different view angles.
- Multiview gait recognition, in which single view probe gait features are recognized with multiview gallery gait feature vector.

Table 7, summarizes the study on view variation and appearance changes, from the year 2015 to July 2018. Figure 20 depicts the average accuracy achieved based on methods proposed by different researchers considering view and appearance change covariates in table 7.

VIII. FUTURE PERSPECTIVES

Many approaches on vision-based gait recognition have been developed and have achieved promising results, but there are still some performance issues that make gait recognition a

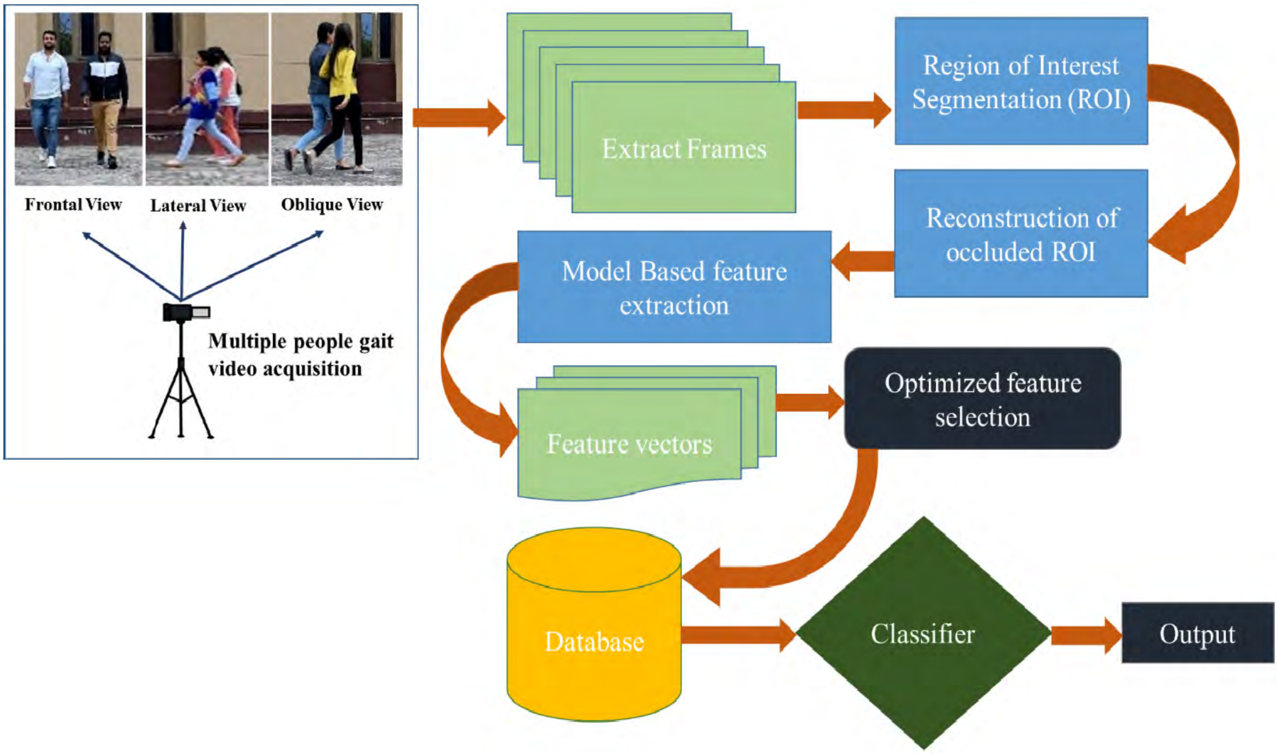

FIGURE 21. Working of proposed system along with sample frames of proposed multigait dataset which include three view directions (Frontal, Lateral, and Oblique).

challenging problem for real-world deployment. Some specific future research perspectives are as follows:

A. GAIT DATASET CREATION

Recently there have been several gait datasets available, but these datasets are vulnerable to geographical and demographic restrictions. In addition to that researchers employ their own rules, even created under constrained environment and available datasets were on single gait.

This extends researchers to a new direction of research, to recognize a probe subject based on gait in real time scenario (for example multiple subjects walking together or in the crowd). This raises a significant challenge, requiring research, i.e., how to handle occlusion (static and dynamic discussed in section VII-A) and moreover, to build a dataset of gait covering occlusion along with existing covariates (such as view variations, carrying conditions, clothing variations, etc.).

B. MULTIVIEW COVARIATE CONDITION

Silhouette based gait recognition is severely affected by view variations and is an open research issue for model-free based gait recognition. Current research algorithm achieved good recognition accuracy under lateral view (side view), but performance is compromised for other view angles. So there can be a possibility to have an effective approach to solve this issue, such as multiple cameras to capture different view sequences and to design sophisticated view-invariant algorithms to cope with the issue of recognizing a particular subject under multiple view angles with less error rate.

C. APPEARANCE CHANGE CONDITIONS

Human natural gait appearance can change due to many factors such as walking surface, footwear type, clothing variations, and carrying conditions, etc. These changes in human gait lead to new research directions for researchers, to identify the unique features that are less sensitive to appearance and may be employed to improve recognition accuracy. This issue can also lead researchers from different regions to create a database that severely affects gait recognition due to appearance change, for example in Indian subcontinent women wear saree (traditional dress) which affects gait patterns as compared to women wearing short skirts, jeans. Such a dataset is still not available to the best of our knowledge.

D. ADAPTIVE BACKGROUND MODELLING

Segmentation of human walking silhouette in unconstrained conditions is still an unsolved problem of automated gait recogntion system. Traditional segmentation of human gait which was still based on background subtraction approaches [28], [29].This leads possibility to have adaptive background modelling for object segmentation and can handle unconstrained conditions like dynamic background, cluttered background, presence of shadows, motion of cameras, inconsistent lighting conditions and occlusion.

E. FEATURE SPACE REDUCTION

Traditional gait based human recognition has mostly been evaluated without explicitly considering the most relevant gait features, which has affected performance. Even genetic algorithm(evolutionary approach) has been used for optimized feature selection [33], but still more work needs to be done for efficiency improvement. To tackle this issue, optimized search approaches (like bioinspired approaches, particle swarm optimization, hybrid approaches, etc.) can be employed to retrieve a subset of relevant features that can improve performance accuracy.

Moreover, Table 8 presents the future work of the current articles published in reputed journals (web of science) from 2015 till July 2018.

IX. PROPOSED WORK

We have proposed to work on gait recognition considering dynamic occlusion under multi gait scenario. This study aims to analyze that the minimum number of frames can be adequate for recognition under dynamic occlusion Objectives of the proposed work are as follows:

1) Creating a dataset of multigait in an unconstrained environment.
2) Considering three view variations (lateral, oblique and frontal) based on [27], shown in Fig. 21.
3) We consider a model based approach because of robustness against view variations, background cluttering, and detection of body segments.
4) Apply a segmentation approach to extract body segments to develop a geometrical model.
5) Reconstruct the occluded objects.
6) Extract model based gait features for individual identification under the multigait scenario.
7) Apply optimization approach for feature selection and also apply soft computing for classification to improve accuracy.

X. CONCLUSION

Gait as a behavioral biometric trait is a dominating research area because of its unobtrusive and non-perceivable characteristics, which can be suitable for visual surveillance monitoring.

This article is an extensive survey of existing research efforts in the area of vision-based gait recognition systems. The article summarized the contribution of various authors in the field of gait analysis from the period of the Renaissance.

In recent years of research, kNN classifier has been dominantly used by authors in their research work for classification. Recently Deep learning has been explored in gait recognition and has achieved promising results, while deep learning required a larger dataset to work.

The article extensively surveys feature extraction approaches in model-based and model-free gait recognition.

The article surveyed the vision-based and sensor gait database created since 1998. OUISIR and CASIA are the largest gait database which considers most covariates factors that affect the gait recognition performance.

After surveying articles on vision based gait recognition from 2012 to July 2018, found that 38% of articles have used CASIA-B dataset for analysis of their proposed model for gait recognition.

Two application areas of gait have been reviewed i.e. soft biometric and clinical diagnosis. These domains defined that how gait analysis helpful for soft biometric (such as gender classification and age estimation) and clinical diagnosis (such as lower limb disorder, Parkinson patient diagnosis, etc.). Still, more research can be needed under these application domain, especially for clinical diagnosis to have an automated system for prediction of gait based diseases at early stages.

After investigating state-of-the-art in human recognition based on gait, it is concluded that more work is desired to be done in order to achieve accuracy under different covariate conditions. The accuracy achieved above 90% has been only under normal walking conditions, but performance falls due to, i.e., view variations, appearance changes, and occlusion. These are the open research issues that can be explored more by researchers.

This paper has provided useful references and investigate approaches proposed in recent years that can be extended for future research in the field of gait recognition and make it applicable for practical deployment.

APPENDIX

Here we provide the URLs for images that are taken from the internet.

Figure 2: http://www.clinicalgaitanalysis.com/history/ancients.htmlhttps://en.wikipedia.org/wiki/Giovanni_Alfonso_Borellihttp://www.scientificlib.com/en/Physics/Biographies/WilhelmEduardWeber.htmlhttps://www.imdb.com/name/nm1155956/http://www.clinicalgaitanalysis.com/history/ww2.htmlhttp://www.clinicalgaitanalysis.com/history/modern.htmlhttp://www.betterphotography.in/perspectives/great-masters/etienne-jules-marey/48592/https://www.nap.edu /read/4779/chapter/14https://www.europeana.eu/portal/en/record/2020801/dmglib_handler_biogr_17004.htmlhttp://cvrc.ece.utexas.edu/aggarwaljk/index.htmlhttps: //me.queensu.ca/People/Deluzio/JAM/files/Baker.pdf.

Figure 6: https://www.bayometric.com/identification-verification-segmented-identification/

Figure 21: https://www.shutterstock.com/imagevector/vector -flat-cartoon-lens-photo-camera- 777796435

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