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Review Article

Robust gait recognition: a comprehensive survey

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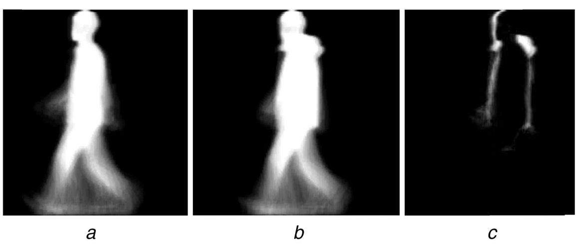
Abstract: Gait recognition has emerged as an attractive biometric technology for the identification of people by analysing the way they walk. However, one of the main challenges of the technology is to address the effects of inherent various intra-class variations caused by covariate factors such as clothing, carrying conditions, and view angle that adversely affect the recognition performance. The main aim of this survey is to provide a comprehensive overview of existing robust gait recognition methods. This is intended to provide researchers with state of the art approaches in order to help advance the research topic through an understanding of basic taxonomies, comparisons, and summaries of the state-of-the-art performances on several widely used gait recognition datasets.

1 Introduction

Recently, a large number of surveillance cameras have been deployed in public areas and significant research efforts have been proposed to develop smart systems capable to capture and analyse visual data in order to extract information relating to suspicious human behaviour and identity. Gait is one of the most suitable behavioural biometric modalities for recognising people especially for video telesurveillance applications [1]. For example, in monitoring scenarios, subjects are usually captured at a distance from the cameras, thus making large part of physiological biometric characteristics not appropriate. The main limitations relate to the viewing angle variations and occlusions which inherently result in the difficulty to capture the whole biometric features. Consequently, physiological traits cannot provide acceptable performances in practical situations. On the other hand, gait, as a behavioural biometric modality, includes individual appearance (i.e. limb and leg length) and dynamic information of the person's walk. Compared to other physiological biometric modalities such as speech, gait can be captured at a distance while still being difficult to imitate or circumvent.

Gait can be defined as the coordinated, cyclic combination of the movements resulting in human locomotion. The coordination and the cyclic nature of the motion make a person's gait unique. Gait recognition can be carried out by extracting some salient properties relating to the coordinated cyclic motions that result in human locomotion. Unfortunately, despite the advantages of gait recognition, it has also some limitations. For examle, it has been demonstrated that gait recognition performances are drastically influenced by different covariates (i.e. intra-class variations) related to the subject itself, such as clothing and carrying conditions; or related to the environment such as view angle variations, walking surface, occlusions, shadows, and segmentation errors [2–4]. Fig. 1 shows an example of intra-class distortions caused by clothing variations of the same subject recorded at instants t and $t + 1$.



a b c

Fig. 1 *Example of intra-class variations caused by clothing variations of the same subject recorded at instant t and t + 1. Image c is the difference of a and b*
(a) Instant t, ***(b)*** Instant $t + 1$, ***(c)*** Intra-class

A considerable amount of interesting reviews related to gait recognition has been proposed [5–11]. However, to the best of our knowledge, none of these surveys paid a particular attention to robust gait recognition dealing with intra-class variations caused by various conditions. This paper aims to give comprehensive survey of recent works on robust gait recognition. The remaining part of this paper is organised as follows. Section 2 summarises the main steps of a gait recognition system. Section 3 explains the model-based approach. Section 4 presents a model-free approach. Section 5 details robust cloth, view angle, and occlusion gait recognition approaches. Section 6 focuses on the main available gait recognition datasets, related state-of-the-art results, and discussions. Finally, Section 7 concludes the paper.

2 Gait recognition systems

Independently of any adopted approach, a gait recognition system consists of three main steps: feature extraction, representation, and classification. While a large variety of features have been proposed by the research community (and which will be introduced later in this survey), the feature representation and classification steps will be discussed in this paper.

2.1 Feature representation

The performance of any recognition system heavily depends on finding a good and suitable feature representation space. However, finding such a suitable representation adapted for data classification is a challenging problem which has taken a huge interest by the machine learning community. Among the existing state-of-the-art feature representation techniques, dimensionality reduction and especially principal component analysis (PCA), linear discriminant analysis (LDA), as well as their combination which have shown their efficiency in tackling the gait recognition problem are widely used.

- Given n d -dimensional samples $\{\boldsymbol{x}_i\}_{i=1}^{n}$ in matrix $\boldsymbol{X} \in \mathbb{R}^{d \times n}$ and a dimensionality choice $r < d$, PCA is an unsupervised linear dimensionality reduction technique formulated as the minimisation of the residual errors between the original and the projected data

$$\min_{\boldsymbol{M} \in \mathbb{R}^{d \times r}} \| \boldsymbol{X} - \boldsymbol{M}\boldsymbol{M}^T\boldsymbol{X} \|_F^2 \quad \text{s.t}\ \boldsymbol{M}^T\boldsymbol{M} = \boldsymbol{I} \tag{1}$$

where $\| \cdot \|_F$ is the Frobenius norm and $\boldsymbol{I}$ is the identity matrix. The solution $\boldsymbol{M}$ corresponds to the r leading principal eigenvectors of $\boldsymbol{X}\boldsymbol{X}^T$ and we get the projection matrix $\boldsymbol{P} = \boldsymbol{M}^T$.

- LDA is a supervised technique which aims to project the data into a lower subspace where the data from different classes are well separated. In other words, the LDA seeks to minimise the intra-class variations and to maximise the between class variations

$$\max_{\boldsymbol{M} \in \mathbb{R}^{d \times r}} \frac{\mathrm{tr}(\boldsymbol{M}^T\Sigma_B\boldsymbol{M})}{\mathrm{tr}(\boldsymbol{M}^T\Sigma_W\boldsymbol{M})} \quad \text{s.t} \quad \boldsymbol{M}^T\boldsymbol{M} = \boldsymbol{I} \tag{2}$$

where Σ_W and Σ_B represent the within and between class scatter, respectively, and tr stands the matrix trace.

2.2 Classification

It can be seen in the gait recognition literature that nearest-neighbour (NN) and support vector machine (SVM) have been widely and successfully used.

- NN achieves good performance, without a priori assumption about the training data distribution. A new sample is assigned to the class label of the training sample with the lowest distance.
- Let us define $\mathscr{H}$ a Hilbert space induced by the kernel $k(.,.)$. The decision function of a binary SVM problem is given by $h(\boldsymbol{a}) = h_0(\boldsymbol{a}) + b$ with $h_0 \in \mathscr{H}$, $b \in \mathbb{R}$ and $\| h \|_{\mathscr{H}}^2 = \| h_0 \|_{\mathscr{H}}^2$ and is obtained as the solution of [12]

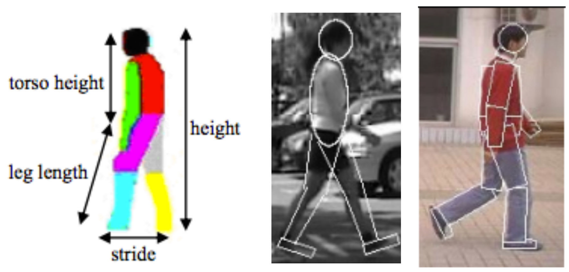
$$\begin{cases} \min_{h_0, b} \dfrac{1}{2} \| h \|_{\mathscr{H}}^2 + C_{\mathrm{svm}} \sum_{n=1}^{N} \xi_n \\ \text{s.t} \quad y_n h(\boldsymbol{a}_n) \geq 1 - \xi_n, \quad \xi_n \geq 0 \quad \forall n = 1, \ldots, N \end{cases} \tag{3}$$

where $\{(\boldsymbol{a}_n, y_n) \in \mathscr{A} \times \{-1, +1\}\}_{n=1}^{N}$ are the labelled training samples. ξ_n and C_{svm} represent slack variables and tuning parameter. To solve our C-class problem one-against-all strategy is mainly applied. It consists of constructing C binary SVM, each one separates a class from all the rest.

3 Model-based gait recognition

In model-based approaches, the feature representatives of a gait are derived from a known structure or fitted model which mimics the human skeleton. Consequently, model-based approaches are based on prior knowledge and often require both a structural and a motion model to capture both static and dynamic information of the gait. The structural models describe the body topology of a person such as stride length, height, hip, torso, and knee. This can be made up of primitive shapes (cylinders, cones, and blobs), stick figures, or arbitrary shapes describing the edge of these body-parts. In the other side, a motion model attempts to describe the dynamics of the motion of each body-part (see Fig. 2).

Existing works in model-based approaches can be broadly divided into two types: those based on the estimation of the body parameters (length, width, cadence etc.) directly from the raw videos and those trying to fit a model to capture the evolution of these parameters over time. In the body parameters estimation approach, Bobick and Johnson [16] proposed to recover static body and stride parameters of a subject's body. Tanawongsuwan and Bobick [17] used the trajectories of joint angles from the body motion. BenAbdelkader *et al.* [18] extracted stride and cadence characteristics of the walking person. Boulgouris and Chi [19] proposed to separate the human body into different components in order to describe the similarity between silhouettes with respect to



a b c

Fig. 2 *Example of body models*
(a) Nixon *et al.* [13], ***(b)*** Wagg *et al.* [14], ***(c)*** Wang *et al.* [15]

a certain body component. Cunado *et al.* [20] obtained the angular information during the walking process from the upper leg using Fourier series. Zeng *et al.* [21] exploited the lower limb joint angles of the side silhouette to characterise the dynamic gait part. Bouchrika *et al.* [22] described a subject's angular motion for both the knee and hip at different phases of the gait cycle. Yeoh *et al.* [23] extracted five joint angular trajectories. Khamsemanan *et al.* [24] exploited the posture-based features. Recently, Deng *et al.* [25] combined both spatio-temporal and kinematic features.

In the case of fitting model approaches, Lee and Grimson [26] exploited the appearance and dynamic traits of gait by analysing the parameters of fitted ellipses to regions of a subject's silhouette. Dockstader *et al.* [27] defined a 3D model to extract various joint angles. Wang *et al.* [15] modelled human body as 14 rigid parts connected to one another at the joints. Zhang *et al.* [28] introduced a non-rigid 2D body contour using a Bayesian graphical model whose nodes correspond to point positions along the contour. Zhang *et al.* [29] suggested a five-link biped human locomotion model to allow for the extraction of the joint position trajectories. Lu *et al.* [30] adopted a full-body layered deformable model to capture information from the silhouette of a walking subject. Ariyanto and Nixon [31] introduced a new 3D model approach using a marionette and mass-spring model. Yoo *et al.* [32] proposed to extract nine coordinates from the human body contours using human anatomical knowledge in order to build a 2D model. Tafazzoli and Safabakhsh [33] combined active contour models and Hough transform to model the movements of the articulated parts of the body. Table 1 summarises the captured features as well as the classifiers of the aforementioned model-based techniques.

Model-based methods seem to be a very attractive concept and are promising since they have the ability to deal with the various intra-class variations caused by different covariates such as clothing, carrying, and view angle which affect the subjects appearance. However, the complexity of the models and the extraction of their components from the video stream is not a trivial task. Consequently, model-based techniques are preferred in practical applications.

4 Model-free gait recognition

Model-free approaches, which can be seen as image measurement methods, exploit the moving shape of the subject to derive the gait characteristics. Therefore, they do not require to rebuild a model of human walking steps. Recently, a number of feature types have been introduced in the context of model-free gait recognition. The features can either be solely based on the moving shape (i.e. no prior shape information is explicitly taken into consideration) or integrated in the shape aspect within the feature representation. Model-free features are categorised as temporal and spatial. However, they can be further organised into four sub-categories: contours, silhouettes, energy, and depth.

- *Contours:* they have low computational cost but suffer from intra-class variations. Symmetry operators introduced by Hayfron Acquah *et al.* [1] are an example of gait recognition-based contour features which are able to form a robust feature representation from a few training samples.
- *Silhouettes:* a whole silhouette is taken into consideration per subject. This can be advantageous because the errors of

silhouette segmentation are avoided. An example of gait recognition based on person silhouette is the self-similarity method based on the silhouettes correlation introduced by BenAbdelkader *et al.* [34].
- *Energy:* energy features attempt to extract the spatial and temporal information of the gait using a single and robust signature. The average image representation along a gait cycle is a good example [35]. In the following, we review the main works in the context of model-free approach.
- *Depth:* instead of using solely colour images, some works tried to exploit depth information based on devices such as Microsoft Kinect [36–38] in order to capture 3D dynamic features. Motivated by its ability to infer the motion of different body-parts, depth features have been combined with other types of features such as colour for more accurate gait recognition [39].

Early on, researchers were more focused on features based on silhouettes and contours [40]. Kale *et al.* [41] utilised the contour width of binarised silhouettes and an entire binary silhouette, too. Liu and Sarkar [42] trained a hidden Markov model (HMM) using manually extracted silhouettes. Kale *et al.* [43] combined the outer contour width of binarised silhouettes with HMMs. Collins *et al.* [44] matched 2D silhouettes extracted from key frames based on correlation. Wang *et al.* [45] introduced a gait signature called 'eigenshape' using Procrustes analysis [46]. The similarity between signatures is measured by Procrustes mean shape distance. Lee *et al.* [47] suggested a shape variation-based frieze pattern signature to capture both horizontal and vertical motion of the walking subject over time. For the recognition phase, a cost function for matching is adopted. Hayfron Acquah *et al.* [1] analysed the human motion symmetry. Discrete Fourier Transform of the signature and NN were adopted for classification. Choudhury and Tjahjadi [48] captured the spatio-temporal shape and dynamic motion information. The matching was carried out through phase-weighted magnitude spectra. Zeng *et al.* [49] approximated the gait dynamics using radial basis function (RBF) networks. Zhang *et al.* [50] represented the extracted silhouettes using sparse and discriminative tensor to vector. Ioannidis *et al.* [37] assigned depth data to the binary silhouettes to enhance accuracy. Lam *et al.* [51] presented static silhouette templates representation to extract both the dynamic and static information. Choudhury and Tjahjadi [52] extracted the features from the silhouette contours using Procrustes shape analysis. Lee *et al.* [53] introduced a novel Fourier descriptor-based gait modelling using the periodic deformation of contours. Deng *et al.* [54] combined silhouette features via deterministic learning. Bengua *et al.* [55] introduced a matrix product state decomposition to compress multidimensional silhouette data represented by higher-order tensors. Tsuji *et al.* [56] proposed a silhouette transformation method. Recently El-Alfy *et al.* [57] encoded both body shapes and boundary curvatures into a novel feature descriptor named normal distance map.

On the other side, some works tried to find an efficient and suitable representation spaces for the extracted features (for both contours and silhouettes) based on supervised and unsupervised representation learning techniques. For example, Wang *et al.* [58] combined 1D normalised distance with PCA in order to reduce the resulting high dimensionality of the feature vectors. Benabdelkader *et al.* [59] captured 3D information (XYT) of the patterns by computing image self-similarity plot corresponding to the images correlation. The combination of PCA and LDA with a NN strategy was adopted for classification. Kobayashi and Otsu [60] extended higher-order local auto-correlation [61] to obtain cubic higher-order local auto-correlation. The classification was carried out using LDA and NN. Lu and Zhang [62] extracted discriminative features from the silhouettes based on Fourier and wavelet descriptors. Independent component analysis with genetic fuzzy SVM classifier was used for recognition. Lu *et al.* [63] applied multilinear PCA combined with LDA to the extracted silhouettes.

Despite the good results of the contour/silhouette features, gait energy image (GEI) representation suggested by Han and Bhanu [4] seems to be more efficient. The technique is based on computing the silhouettes average over a complete gait cycle. It makes a good trade off between the computational complexity and the recognition performance. For the recognition process, it was initially combined with canonical discriminant analysis. It actually corresponds to PCA followed by LDA combined with a NN. PCA aims to retain the most representative information while suppressing noise, whereas LDA tries to determine a set of features that can best distinguish various objects. Following the work of Yu *et al.* [3] which applied a template matching on GEIs, a considerable amount of works in the literature tried to find a good and suitable feature representation space for classification. Motivated by the problem caused by the vectorisation of the feature vectors when using conventional dimensionality reduction techniques which leads to under sample problem, tensor-based dimension reduction methods have been introduced. Xu *et al.* [64] adopted two supervised and unsupervised subspace learning methods: coupled subspaces analysis (CSA) and discriminant analysis with tensor representation (DATER) in order to efficiently represent GEIs. Tao *et al.* [65] used Gabor filters to extract discriminative features from GEI templates. general tensor discriminant analysis (GTDA) is applied instead of the PCA technique. Influenced also by the advantages of tensor-based dimensionality reduction, Xu *et al.* [66] presented an extension of

Table 1 Overview of model-based methods (features and classifiers)

Method	Features	Classification
• Bobick and Johnson [16]	length, width, stride	NN
• Tanawongsuwan and Bobick [17]	joint-angle trajectories	NN
• Benabdelkader *et al.* [18]	stride, cadence	Bayesian
• Cunado *et al.* [20]	motion upper leg	NN
• Boulgouris and Chi [19]	body components	metric-based body-parts
• Zeng *et al.* [21]	lower limb joint angles	RBF neutral network
• Bouchrika *et al.* [22]	angular motion of knee and hip	NN
• Yeoh *et al.* [23]	five joint angular trajectories	SVM
• Deng *et al.* [25]	width, joint-angle trajectories	NN
• Khamsemanan *et al.* [24]	posture features	NN
• Lee and Grimson [26]	parameters of fitted ellipse model	SVM
• Dockstader *et al.* [27]	various joint angles	NN
• Wang *et al.* [15]	rigid model (joint angles)	NN
• Zhang *et al.* [28]	non-rigid model (deformations)	chain-like model
• Zhang *et al.* [29]	5-link model (joint-trajectories)	hidden Markov models
• Lu *et al.* [30]	deformable model (orientations)	dynamic time warping
• Yoo *et al.* [32]	2D model (periodic motion)	neural network
• Tafazzoli and Safabakhsh [33]	anatomy model (arm movement)	NN
• Ariyanto and Nixon [31]	3D model (motion)	NN

Table 2 Overview of GEI-based methods (features, transformations, and classifiers)

Reference	Features	Transformation	Classification
• Han and Bhanu [4]	GEI	PCA + LDA	NN
• Yu *et al.* [3]	GEI	—	NN
• Xu *et al.* [64]	GEI	CSA + DATER	NN
• Tao *et al.* [65]	GEI + Gabor	GTDA + LDA	NN
• Xu *et al.* [66]	GEI	MFA	NN
• Chen *et al.* [68]	GEI + Gabor	TRIMAP	NN
• Huang *et al.* [69]	GEI + Gabor	—	image-to-class distance
• Zhang *et al.* [70]	GEI	SR + MTP	NN
• Xu *et al.* [71]	GEI + Augmented Gabor	—	LGSR
• Lai *et al.* [72]	GEI	SBDA	NN
• Lu *et al.* [73]	GEI	SRML	NN
• Martin *et al.* [74]	GEI	Transfer learning (RankSVM)	SVM
• Lishani *et al.* [75]	GEI + Haralick	Gaussian	SVM
• Guan *et al.* [76]	GEI	RSM (2DPCA + 2DLDA)	NN
• Xing *et al.* [77]	GEI	C3A	NN
• Rida *et al.* [78]	GEI	SD + GLPP	NN
• Lishani *et al.* [79]	GEI + Gabor	SRKDA	SVM
• Wang *et al.* [80]	GEI + Gabor wavelets	2DPCA	SVM
• Ma *et al.* [81]	GEI	TSEL_TCB	NN
• Ma *et al.* [82]	GEI	KSEL_TCB	NN
• Ben *et al.* [83]	Low resolution GEI	NCMs	NN
• Chen and Xu [84]	GEI	SCMHLRR	ranking
• Chhatrala *et al.* [86]	GEI	SMLDA	LGSR

marginal Fisher analysis (MFA). Li *et al.* [67] defined a new manifold learning technique named discriminant locally linear embedding. Chen *et al.* [68] introduced a tensor-based Riemannian manifold distance-approximating projection (TRIMAP). Huang *et al.* [69] introduced an image-to-class distance for comparison. Zhang *et al.* [70] combined super resolution (SR) algorithm with multilinear tensor-based learning without tuning parameters (MTP) to tackle the problem of low resolution GEIs. Xu *et al.* [71] combined the local augmented Gabor GEI features with locality-constrained group sparse representation (LGSR). Lai *et al.* [72] introduced a matrix-based sparse bilinear discriminant analysis (SBDA) to explore the more powerful discriminant subspaces. Lu *et al.* [73] exploited discriminative information by proposing a sparse reconstruction-based metric learning (SRML) metric to minimise and maximise intra- and inter- class sparse reconstruction errors, respectively. Martin and Xiang [74], introduced a bipartite ranking algorithm for improved generalisation of unseen gait scenarios. Lishani *et al.* [75] extracted Haralick features which are fed to a non-linear SVM classifier. Guan *et al.* [76] introduced an efficient ensemble classifier method. Xing *et al.* [77] introduced complete canonical correlation analysis (C3A) to tackle the drawbacks of canonical correlation analysis (CCA). Rida *et al.* [78] applied statistical dependency (SD) feature selection followed by globality-locality preserving projections (GLPP). Lishani *et al.* [79] extracted features from GEIs using a bank of Gabor filters, then the resulting features were combined with spectral regression Kernel discriminant analysis (SRKDA). Wang *et al.* [80] projected the GEI Gabor wavelet features in a new subspace using 2DPCA. Ma *et al.* [81] tried to find a discriminative low-dimensional subspace based on tensor subspace ensemble learning totally corrective boosting (TSEL_TCB) as well as its kerneled version KSEL_TCB [82]. Ben *et al.* [83] presented a novel non-linear coupled mappings (NCMs) for low resolution GEI-based recognition. Chen and Xu [84] introduced sparse coding multi-view hypergraph learning re-ranking (SCMHLRR) for the uncooperative setting. Lee *et al.* [85] adopted a probabilistic SVM. Recently, Chhatrala *et al.* [86] introduced sparse multilinear Laplacian discriminant analysis (SMLDA). Table 2 summarises the different features, transformations and classifiers for GEI-based gait recognition techniques.

5 Robust model-free gait recognition

Despite its attractive performances, the GEI images including features extracted from model-free suffer from intra-class variations caused by different covariates such as clothing conditions, carrying, and view angle variations which drastically influence the recognition performances. Silhouettes segmentation and view angle variations represent further causes of the recognition errors [2–4].

5.1 Clothing robust

People wear different clothes depending on days and seasons. Unfortunately, the intra-class distortions of the static features caused by the variations of clothing can significantly affect the accuracy of the recognition process. Matovski *et al.* [2] have shown that clothing variations are the main factor that drastically affects the performance accuracy. Thus, this makes sense to reduce the effect of clothing distortions in order to improve the performances. To overcome these limitations resulting from clothing variations, several approaches have been proposed. They can be broadly divided in two groups: the first one aims to improve GEIs by selecting the discriminative gait parts while the second introduces feature representations based on GEI gaps.

5.1.1 Gait parts feature-based representations: In this approach, the methods attempt to use some body-parts in order to perform the recognition. Depending on the employed segmentation and selection method, the techniques can be organised into four sub-categories: anatomical-based, self-defined, learning-based, and cloth-based methods (see Table 3).

- Anatomical-based methods seek to segment the body into different parts according to anatomical properties of the human body [112]. Examples of this type of methods are described in [87, 89–91]. This approach is easy to implement, however, the segmentation proportions are anatomical-based and cannot be modified for different clothing length, leading to lower accuracy in case of some specific clothes.
- Self-defined methods select a few hand-crafted body-parts based on human knowledge. The selected parts are presumed to be robust to clothing variations. Li and Chen [92] used the head and feet to construct GEIs. Gabriel *et al.* [94] selected only the lower part of the human body. Lishani *et al.* [97] proposed to

divide GEI into horizontal and vertical equal parts and then the best region of interest is selected. Nandy *et al.* [96] proposed to decompose a GEI into vertical and horizontal independent structural segments. Iwashita *et al.* [93] divided GEI into multiple areas according to their invariance to appearance changes. Islam *et al.* [95] divided the human body into very small windows. Unfortunately, such type of methods fails to predict all possible cases of clothing variations in more complicated real application scenarios.

- Learning-based methods seek to find discriminative body-parts based on machine learning techniques. Feature selection and especially wrapper approaches have received a special interest from the research community. Starting from the original feature set, all possible feature subsets obtained by search algorithms are evaluated. The prediction performance serves as a selection criterion, and the subset that performs the best is retained. Different techniques have been used including NN [98, 100–102] and modified phase only correlation [104]. In addition to previous techniques, random forest rank features [99], group fused Lasso [105, 106, 113], SD [78], gini impurity [107, 108], and genetic algorithm [109] have been also investigated. Another trend is to estimate the position of covariates in order to remove them. Whytock *et al.* [103] proposed a novel bolt-on module enabling to improve the robustness using various single compact 2D gait representations including GEI. Recently, Ghebleh and Ebrahimi [110] introduced an adaptive outlier detection method to address the effects of clothing issue. Learning methods are robust and able to achieve good accuracy. However, they have high computation cost and need a considerable amount of gallery data in various conditions in order to learn the body-parts.
- Cloth-based methods attempt to segment the body into parts based on the cloth characteristics. Liang *et al.* [111] proposed a golden ratio segmentation method which has shown very promising results in case of clothing variations. However, the method strongly depends on cloth and may not cope with the intra-class variations caused by other conditions.

5.1.2 Clothing robust feature representations: In order to mitigate the effects of clothing variations in model-free features and especially GEIs, several variations of GEIs have been proposed. Liu and Zheng [114] introduced motion history image representation which is able to capture dynamic gait characteristics. Ma *et al.* [115] suggested gait moment image which represents the probability of an image at each key frame. Yang *et al.* [116] used a variation analysis to obtain GEI regions which allow to better reflect the walking manner. Chen *et al.* [117] introduced a robust representation called frame difference energy image capable to preserve the kinetic information. Bashir *et al.* [118] suggested gait flow fields approach using a weighted sum of the optical flow. While existing works are focused on casual clothes, Shanableh *et al.* [119] proposed an accumulated prediction image suitable for both casual and Gulf clothes. Bashir *et al.* [120] introduced gait entropy image by calculating the entropy of each pixel. Wang *et al.* [121, 122] proposed a temporal template called chrono-gait image (CGI). Zhang *et al.* [123] adopted Active energy image focusing on dynamic regions by extracting the active regions of a gait sequence. Lam *et al.* [124] determined the optical flow field between two consecutive silhouettes in order to obtain gait flow image. Roy *et al.* [125] extracted pose energy image features corresponding to the average of all the silhouettes. Hofmann and Rigoll [126] proposed to average the cycles over full gait cycles to reduce the noise, then histogram of oriented gradient (HOG) is applied in order to obtain gradient histogram energy image. Huang and Boulgouris [127] adopted shifted energy image and gait structural profile. Jeevan *et al.* [128] encoded the randomness of the silhouette images using Pal and Pal entropy. Boulgouris and Chen [129] introduced radon energy image. Lee *et al.* [130] calculated the binomial distribution of every pixel in order to obtain gait probability image. Kusakunniran [131, 132] detected points of interest, then discriminative features are extracted based on HOG and histogram of optical flow in the neighbourhood of each detected point of interest. Arora and Srivastava [133] proposed a gait period dependent image, which is calculated over a gait cycle based on Gaussian membership function. Luo *et al.* [134] suggested a new class energy image which can reflect the time characteristics denoted as the accumulated frame difference energy image. Al Tayyan *et al.* [135] introduced the concept of accumulated flow image and edge-masked active energy image able to produce distinctive features for classification. Lee *et al.* [136] proposed a combination of spatio-temporal approach and texture descriptors to extract discriminative gait features named

Table 3 Overview part-based clothing robust gait recognition

Reference	Year	Part-based methods
• Hossain *et al.* [87]	2010	anatomical properties
• Li *et al.* [88]	2010	anatomical properties
• Choudhury and Tjahjadi, [89]	2015	anatomical properties
• Verlekar *et al.* [90]	2017	anatomical properties
• Aggarwal and Vishwakarma [91]	2017	anatomical properties
• Li and Chen [92]	2013	self-defined
• Iwashita *et al.* [93]	2013	self-defined
• Gabriel *et al.* [94]	2013	self-defined
• Islam *et al.* [95]	2013	self-defined
• Nandy *et al.* [96]	2016	self-defined
• Lishani *et al.* [97]	2017	self-defined
• Bashir *et al.* [98]	2008	wrapper
• Dupuis *et al.* [99]	2013	random forest
• Rida *et al.* [100]	2014	wrapper
• Rida *et al.* [101]	2015	wrapper
• Rokanujjaman *et al.* [102]	2015	wrapper
• Whytock *et al.* [103]	2015	bolt-on module
• Rida *et al.* [104]	2016	wrapper
• Rida *et al.* [105, 106]	2016	group fused Lasso
• Rida *et al.* [78]	2016	SD
• Alotaibi and Mahmood [107, 108]	2016	Gini impurity
• Issac *et al.* [109]	2017	genetic algorithm
• Ghebleh and Ebrahimi [110]	2017	adaptive outlier detection
• Liang *et al.* [111]	2016	cloth proportion

Table 4 Overview of clothing robust representations for gait recognition (features, transformations, and classifiers)

Reference	Year	Features	Transformation	Classification
• Boulgouris and Chen [129]	2007	radon energy image	LDA	NN
• Liu and Zheng [114]	2007	motion history image	LDA	NN
• Ma *et al.* [115]	2007	gait moment image	—	NN
• Yang *et al.* [116]	2008	enhanced GEI	discriminative common vectors	NN
• Chen *et al.* [117]	2009	frame difference energy image	—	HMM
• Bashir *et al.* [118]	2009	gait flow fields	PCA + LDA	NN
• Shanableh *et al.* [119]	2009	accumulated prediction image	—	Polynomial networks
• Bashir *et al.* [120]	2010	GEI	PCA + LDA	NN
• Wang *et al.* [121, 122]	2010	CGI	PCA + LDA	NN
• Zhang *et al.* [123]	2010	active energy image	2DLPP	NN
• Mu *et al.* [141]	2010	C1Gait	discriminative locality alignment	NN
• Lam *et al.* [124]	2011	gait flow image	LDA	NN
• Roy *et al.* [125]	2012	pose energy image	PCA + LDA	NN
• Hofmann and Rigoll [126]	2012	gradient histogram energy image	PCA + LDA	NN
• Huang *et al.* [127]	2012	shifted energy image + gait structural profile	LDA	NN
• Liu *et al.* [149]	2012	multiple HOG	PCA + LDA	NN
• Jeevan *et al.* [128]	2013	gait pal and pal entropy	PCA	SVM
• Hu *et al.* [148]	2013	LBP flow	—	HMM
• Lee *et al.* [130]	2014	gait probability image	—	minimum Kullback–Leibler
• Kusakunniran [131]	2014	histogram of optical flow + HOG	—	NN
• Kusakunniran [132]	2014	histogram of optical Flow + HOG	—	SVM
• Lee *et al.* [137]	2014	time-sliced averaged motion history image	—	majority voting
• Chen and Liu [145]	2014	gait differential image	2DPCA	NN
• Arora and Srivastava [133]	2015	gait Gaussian image	—	NN
• Arora *et al.* [150]	2015	gradient histogram Gaussian image	—	NN
• Lee *et al.* [136]	2015	transient binary patterns	—	majority voting
• Luo *et al.* [134]	2015	accumulated frame difference energy image	—	NN
• Arora *et al.* [138]	2015	gait information image with energy feature/ sigmoid feature	—	NN
• Choudhury and Tjahjadi [139]	2016	averaged gait key-phase image	PCA	rotation forest ensemble
• Chhatrala and Jandhav [144]	2016	Gabor cosine features	MLDA	LGSR
• Medikonda *et al.* [147]	2016	generalised new entropy	—	SVM
• Al *et al.* [135]	2017	accumulated flow image + edge-masked active energy image	MPCA + LDA	NN
• Atta *et al.* [140]	2017	5/3 gait image	PCA	NN
• Chaurasia *et al.* [143]	2017	$P_{RW}D_F$ GEI	PCA + generalised LDA	NN
• Verlekar *et al.* [146]	2017	sparse error gait image	—	NN

transient binary patterns. Lee *et al.* [137] applied HOG to time-sliced averaged motion history image in order to extract discriminative features. Arora *et al.* [138] proposed gait information image with energy feature and gait information image with sigmoid feature. Choudhury and Tjahjadi [139] computed the average at each of the key-phases to obtain averaged gait key-phase image. Atta *et al.* [140] presented a temporal template approach based on lifting 5/3 wavelet filters named 5/3 gait image. Mu and Tao [141] introduced a biologically inspired feature representation called C1Gait using C1 units corresponding to the complex cells in human visual cortex. Hu *et al.* [142] proposed periodicity feature vector representation to better capture periodic dynamic information. Chaurasia *et al.* [143] suggested a robust gait feature representation called $P_{RW}D_F$ GEI using the fusion of static (not affected by intra-class variations) and dynamic parts of gait information. Chhatrala and Jadhav [144] proposed Gabor cosine features representation. Based on the previous idea of silhouettes difference, Chen and Liu [145] suggested average gait differential image representation. Verlekar *et al.* [146] presented the so called sparse error gait image representation. Medikonda *et al.* [147] introduced generalised new entropy representation. Hu *et al.* [148] proposed an incremental representation based on optical flow named LBP Flow. Liu *et al.* [149] generated multiple HOG template by applying HOG to GEI and CGI. Arora *et al.* [150] introduced a spatial-temporal representation called gradient histogram Gaussian image. It should be also noted that gait was combined with face in order to achieve higher accuracy [151–153]. Table 4 summarises the different features, transformations and classifiers for cloth-robust gait representations.

5.2 Viewing robust recognition

This section provides a review of research efforts carried out to address the problems associated with the view changes in gait recognition. The techniques dealing with view variations can be broadly divided into five categories: view-transformation, view-invariant subspace, view-invariant feature, view-angle estimation, and 3D information.

- View-transformation methods seek to map the features from a different view angles into a common one using view transformation model (VTM). A large variety of transformation models have been proposed through singular value decomposition (SVD) matrix factorisation [154–158], regression using support vector regression [159], elastic net [160], and multilayer perceptron [161]. Muramatsu *et al.* [162] presented an arbitrary VTM using a 3D gait volume. In the same context, Muramatsu *et al.* [163] proposed a generative approach which is a VTM-based method using transformation consistency measures (TCM+).
- View-invariant subspace methods aim to find a transformation that maps the original gait features into a subspace (usually of lower-dimension) in order to obtain view-invariant features.

Huang and Boulgouris [164] constructed a shared space in which different weights were assigned based on the importance of views. Bashir *et al.* [165] adopted a CCA. Liu *et al.* [166] proposed a joint subspace learning method with CCA and PCA. Xu *et al.* [167] presented a coupled locality preserving projections (CLPP) method. Hu [168] exploited regularised local tensor discriminant analysis. Lu *et al.* [169] introduced a supervised manifold learning algorithm called uncorrelated discriminant simplex analysis (UDSA) in order to project gait features extracted from different views into a low-dimensional subspace. Hu [170] adopted uncorrelated multilinear sparse local discriminant canonical correlation analysis (UMSLDCCA). Al Mansur *et al.* [171] proposed to use multi-view discriminant analysis (MvDA) and its tensor version (MvDATER) [172]. Connie *et al.* [173, 174] exploited Grassmann and Grassmann doubly-kernel manifold. Liu *et al.* [175] attempted to exploit more efficiently the discriminative information from these subspaces by applying marginal CCA. Hur *et al.* [176] proposed to tackle the problem of view angle variations using a manifold learning-based approach.

- View-invariant feature methods seek to extract invariant features to view angle variations [177]. Jean *et al.* [178, 179] computed invariant trajectories. Goffredo *et al.* [180] estimated joint positions. Kusakunniran *et al.* [181] normalised the silhouettes into a common canonical view. Zeng and Wang [182] combined silhouette features representing gait dynamics and deterministic learning theory. Castro *et al.* [183, 184] used motion descriptors based on sampled trajectories.
- View-angle estimation methods consist of two main steps. The first one estimates the pose of the query sample to find the gallery samples with the similar pose. The second one identifies the query subject among the gallery samples with the same pose. Various pose estimation techniques have been used. For example, Verlekar *et al.* [90] computed perceptual hash of leg region combined with Hamming distance. Isaac *et al.* [109] applied Bayes' rule to the selected gait part using a genetic algorithm. Rida *et al.* applied NN to the discriminative selected gait parts using group fused Lasso method. Dupuis *et al.* [99] adopted a decision tree approach to the lower parts of GEI. Choudhury and Tjahjadi [89] combined Entropy, 2DPCA and NN to the lower body-part. Zhao *et al.* [185] employed transformation invariant low-rank texture combined with extreme learning machine.
- 3D information-based methods seek to extract discriminative information incorporating 3D information from a set of cameras. Bodor *et al.* [186] used captured video to build 3D view-independent representation. Zhao *et al.* [187] used video sequences captured by multiple cameras to build a 3D human model. Zhang and Troje [188] adopted a 3D linear model. Tang *et al.* [189] reconstructed a 3D parametric body to tackle large view angle change. Luo *et al.* [190] proposed a 3D reconstruction and virtual posture synthesis. Lopez-Fernandez *et al.* [191] introduced a descriptor for the sequences of gait volumes referred to as gait entropy volume which is robust to viewpoint changes and unconstrained curved trajectories. In the same context, Lopez-Fernandez *et al.* [192] presented a 3D angular movement of the subject. The different approaches are summarised in Table 5.

5.3 Occlusion robust recognition

Most approaches in the literature do not treat the quality problem of silhouettes by assuming the absence of occlusions at the time of capture of gait or by taking into consideration several cycles where the non-occluded parts can compensate for the occluded ones. However, in outdoor real-life applications occlusion is omnipresent, for instance, several persons can be captured at the same time leading to occlusions of the subjects. Another cause of occlusion is the presence of non-living objects such as beams and cars. This clearly shows the need to pay more research efforts to tackle this problem. Among the few existing works, Roy *et al.* [193] tried to find gait cycles containing occlusions and improve the corresponding silhouettes using balanced Gaussian process dynamical model. In the same context, Roy *et al.* [194] proposed a model in order to detect the position of occlusions. Ortells *et al.* [195] introduced a novel statistical method to tackle the problem of corrupted silhouettes.

5.4 Towards feature learning approaches

A growing and intensive body of research has recently been observed with the goal to develop end-to-end recognition systems from feature extraction, representation, and classification using deep learning concept. The approaches proceed by using raw data as input features by stacking more than the usual two neural layers of conventional artificial neural networks. In this new concept, each low level layer encodes specific properties of the data as primitives that are gradually combined by successive higher level layers in order to produce representative and hopefully more discriminative representations of the input data thus resulting in much improved performances.

Among the deep learning models applied to gait recognition, convolutional neural networks have been proposed to represent gait with invariance property [196–198], deep Boltzman machine to provide a generative model [199], bidirectional long short-term memory to take into account the temporal information [200], stacked progressive auto-encoders [201] and generative adversarial networks [202] in order to learn invariant features. To be effective deep models require a huge amount of data especially for the training phase in order to provide much improved performances. As such such models are seen to have complex structures requiring significant computing power to attain higher performances.

6 Datasets, performances, and discussions

The availability of large and public datasets is essential for a comparative study of the performances including a consistent evaluation. A comprehensive review of the main free available gait datasets for evaluation including the comparison of the state-of-the-art performances arranged in order of publication year is given in this section.

6.1 Datasets and performances

6.1.1 USF HumanID: USF HumanID is an outdoor dataset [http://figment.csee.usf.edu/GaitBaseline/] [203]. It contains 122 subjects recorded under several covariates: viewpoints (left and right), shoes (A and B), surfaces (grass and concrete), carrying conditions (with and without briefcase), time (May and Nov), and clothing. There are 12 evaluation experiments summarised in Table 6. The main obtained results on USF database are shown in Table 7.

6.1.2 CASIA dataset B: CASIA dataset B is an indoor multi-view dataset [http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp] [3]. It is constructed to evaluate the ability of the algorithms/methods to manage the carrying conditions, clothing and view angles distortions. 124 subjects were recorded from 11 different view angles. Each subject is recorded six times under normal conditions (NL), twice under carrying bag conditions, and twice under clothing variation conditions (CL). The gallery contains the first four normal sequences for each subject and remaining one as used as a probe. The main results obtained using this dataset are summarised in Table 8.

6.1.3 OU-ISIR (dataset B): OU-ISIR (dataset B) was built to study the effect of clothing [http://www.am.sanken.osaka-u.ac.jp/BiometricDB/GaitTM.html] [87, 205]. 48 subjects were recorded on a treadmill under 32 types of clothes listed in Table 9. The gallery set contains subjects in normal clothes (type 9), whereas the probe set contains subjects in the other 31 clothes types. Table 8 depicts state-of-art performances using this dataset.

6.1.4 CMU motion of body (moBo): CMU Motion of Body (MoBo) consists of 25 subjects [https://www.ri.cmu.edu/

Table 5 Overview of view-invariant gait recognition techniques

Reference	Year	Characteristics	Remarks
• Makihara *et al.* [154]	2006	VTM through SVD of frequency-domain features	
• Kusakunniran *et al.* [155]	2009	VTM through SVD	(+) robust cross-view capability
• Kusakunniran *et al.* [159]	2010	VTM using support vector regression	(−) low accuracy in large view difference
• Zheng *et al.* [156]	2011	robust VTM using robust PCA	(+) no complicated camera setup
• Muramatsu *et al.* [157]	2012	VTM through SVD	(−) prior knowledge target view
• Kusakunniran *et al.* [161]	2012	VTM through multilayer perceptron	
• Kusakunniran *et al.* [160]	2012	sparse regression VTM using elastic net	
• Muramatsu *et al.* [162]	2015	VTM using 3D gait volume	
• Muramatsu *et al.* [163]	2015	VTM-based with TCM +	
• Muramatsu *et al.* [158]	2016	incorporating quality measures to VTM	
• Huang *et al.* [164]	2008	shared space with weighted views importance	
• Bashir *et al.* [165]	2010	correlation-based CCA	
• Lu *et al.* [169]	2010	UDSA	
• Hur *et al.* [176]	2010	manifold learning	
• Liu *et al.* [166]	2011	joint subspace learning (CCA + PCA)	(−) accuracy affected by occlusion
• Liu *et al.* [175]	2013	marginal CCA	(+) no complicated camera setup
• Hu [168]	2013	regularised locally tensor discriminant model	(−) require good training data
• Hu *et al.* [170]	2014	UMSLDCCA	(+) good accuracy in large databases
• Al Mansur *et al.* [171]	2014	MvDA	
• Makihara *et al.* [172]	2015	multi-view DATER	
• Connie *et al.* [173]	2016	Grassmann doubly-kernel	
• Xu *et al.* [167]	2017	CLPP	
• Connie *et al.* [174]	2017	Grassmann manifold	
• Jean *et al.* [178, 179]	2009	normalised 2D trajectories	
• Goffredo *et al.* [180]	2010	features-based joint positions	(+) no complicated camera setup
• Kusakunniran *et al.* [181]	2013	normalised silhouettes-based invariant low-rank	(−) perform better in limited view angles
• Castro *et al.* [183, 184]	2014	densely sampled short-term trajectories	
• Zeng and Wang [182]	2016	ilhouettes with deterministic learning	
• Dupuis *et al.* [99]	2013	decision tree	
• Choudhury *et al.* [89]	2015	entropy + 2DPCA + nearest-neighbor	(−) need training data in all angles
• Rida *et al.* [105]	2016	group fused Lasso + nearest-neighbor	(+) simple to implement
• Zhao *et al.* [185]	2016	transformation invariant low-rank texture + extreme learning machine	
• Isaac *et al.* [109]	2017	genetic algorithm + Bayes' rule	
• Verlekar *et al.* [90]	2017	perceptual hash + hamming distance	
• Zhang and Troje [188]	2005	3D linear model of Fourier representations	
• Zhao *et al.* [187]	2006	3D model using multiple cameras	
• Bodor *et al.* [186]	2009	3D model-based combination of views	(−) require complicated cameras calibration
• Lopez-Fernandez *et al.* [191]	2015	gait entropy volume	(+) perform good in large view angles
• Luo *et al.* [190]	2016	parametric 3D model	
• Lopez *et al.* [192]	2016	3D angular information	
• Tang *et al.* [189]	2017	parametric 3D model	

Table 6 Experiments on USF dataset

	Experiments											
	1	2	3	4	5	6	7	8	9	10	11	12
# sequences	122	54	54	121	60	121	60	120	60	120	33	33
variation	V	S	VS	R	RS	RV	RSV	B	BS	BV	TSC	RTSC

V: View; S: Shoe; R: Surface; B: Briefcase; T: Time; AND C: clothes.

publications/the-cmu-motion-of-body-mobo-database/] [206]. Each one was recorded six times in four different conditions: slow/fast walk, inclined walk, and slow walk holding a ball. The list of experiments and accuracies are summarised in Tables 10 and 11, respectively.

6.2 Discussion

From the works described above, it can be seen that both CASIA B and Human ID datasets have been widely used for the evaluation. While very high and competitive accuracies have been obtained using in the former, Human ID dataset still remains very challenging. Therefore, more works are required to obtain superior performances especially in the case of elapsed time which potentially also includes several covariates such as clothing and carrying condition.

It should be noted that the segmentation quality of data in Human ID dataset is poor and needs improvement. Unfortunately, model-free approaches performance strongly depends upon the segmentation quality. Consequently, an interesting work to carry out will be to improve the quality of extracted silhouettes using advanced segmentation techniques. It can be noticed that low performances have been obtained in the experiments 11 and 12 (Table 7). This is due to the elapsed time (6 months) between the recorded gallery and probe gait sequences which affects the performances in an unpredictable manner. Indeed, the elapsed time is still a very challenging problem which potentially also includes the changes of the shoes, carrying status, clothing, lighting conditions etc. It can also be observed that there is a lack of large datasets containing outdoor real-life complicated scenarios such as cluttered background, anthropometric variations, and partial as well as full occlusions. Thus, the need to build new datasets.

It can also be observed that there is no universal feature representation for gait recognition but rather a large variety of features have been proposed and used. Despite their attractive discriminative ability, most features are highly related to the human expertise. In order to improve the discriminative power, existing methods aim to find suitable feature representation spaces where observations from different classes are well separated. For the latter, different approaches such as dimensionality reduction and feature selection have been studied and applied.

Table 7 Accuracy on the human ID gait challenge dataset in per cent

		Experiments											
		1	2	3	4	5	6	7	8	9	10	11	12
Kale *et al.* [41]	2004	89	88	68	35	28	15	21	85	80	58	17	15
Sarkar *et al.* [203]	2005	73	78	48	32	22	17	17	61	57	36	3	3
Han and Bhanu [4]	2006	90	91	81	56	64	25	36	64	60	60	6	15
Xu *et al.* [64]	2006	89	93	80	44	45	25	33	80	79	60	18	21
Liu and Sarkar [42]	2006	85	89	72	57	66	46	41	83	79	52	15	24
Ioannidis *et al.* [37]	2007	83	86	78	39	34	20	21	43	40	40	16	5
Ma *et al.* [115]	2007	84	91	70	26	29	14	16	64	64	42	9	6
Xu *et al.* [66]	2007	89	94	80	44	47	25	33	85	83	60	27	21
Lam *et al.* [51]	2007	77	83	69	12	13	9	12	38	33	19	39	9
Tao *et al.* [65]	2007	91	93	86	32	47	21	32	95	90	68	16	19
Yang *et al.* [116]	2008	90	87	80	41	48	27	28	72	63	63	6	6
Li *et al.* [67]	2008	90	89	81	40	50	27	26	65	67	57	12	18
Chen *et al.* [68]	2010	92	94	86	44	52	27	33	78	74	65	21	15
Hu *et al.* [142]	2010	99	97	94	66	69	52	59	92	91	84	28	35
Guha and Ward [204]	2010	89	85	74	30	22	12	22	87	73	52	6	9
Huang *et al.* [69]	2010	93	89	81	54	52	32	34	81	78	62	12	9
Mu and Tao [141]	2010	95	92	88	45	47	34	34	78	74	65	25	19
Lam *et al.* [124]	2011	82	89	76	27	27	10	17	60	57	54	15	3
Roy *et al.* [125]	2012	85	94	78	49	33	22	26	71	69	47	12	12
Hofmann *et al.* [151]	2012	93	85	81	56	45	38	31	89	90	82	3	6
Hofmann and Rigoll [126]	2012	98	93	87	94	86	62	50	94	91	85	12	12
Kusakunniran *et al.* [161]	2012	89	—	—	—	—	—	—	—	—	—	—	—
Liu *et al.* [149]	2012	96	91	83	33	33	18	25	91	82	82	9	6
Xu *et al.* [71]	2012	95	93	89	62	62	39	38	94	91	78	21	21
Choudhury and Tjahjadi [52]	2012	92	95	84	72	68	29	40	69	60	64	20	18
Wang *et al.* [122]	2012	91	93	78	51	53	35	38	84	78	64	3	9
Choudhury and Tjahjadi [48]	2013	93	96	86	70	69	39	37	78	71	66	27	22
Hu [168]	2013	93	93	90	56	53	36	30	97	90	72	11	17
Kusakunniran *et al.* [181]	2013	85	—	—	—	—	—	—	—	—	—	—	—
Lu *et al.* [73]	2014	93	94	85	52	52	37	40	86	85	68	18	15
Martin and Xiang [74]	2014	83	94	82	60	54	48	42	67	61	55	59	27
Lai *et al.* [72]	2014	93	94	85	51	50	29	36	85	83	68	18	24
Guan *et al.* [76]	2015	100	95	94	73	73	55	64	97	99	94	42	42
Zhang *et al.* [50]	2015	95	88	71	41	28	26	24	-	-	-	-	-
Choudhury and Tjahjadi [89]	2015	95	96	86	54	57	34	36	91	90	78	31	28
Xing *et al.* [77]	2016	88	—	—	—	—	—	—	—	—	—	—	—
Ben *et al.* [83]	2016	69.9	66.6	44.7	39.4	34.8	25.8	20.9	51.9	41.7	36.7	6.8	5.8
Choudhury and Tjahjadi [139]	2016	96	96	90	62	63	37	39	94	93	80	41	32
Chhatrala and Jandhav [144]	2016	98	92	85	64	60	45	36	85	92	90	38	38
Chen and Xu [84]	2016	97	98	92	78	76	75	70	84	82	80	78	61
Wolf *et al.* [197]	2016	89	84	90	83	78	81	83	83	86	78	76	80
El-Alfy *et al.* [57]	2017	93	89	87	41	43	28	36	83	79	80	3	9
Aggarwal and Vishwakarma [91]	2017	97	96	93	68	64	34	37	96	92	86	27	24
Ma *et al.* [81]	2017	95	91	78	66	59	46	52	93	88	69	30	27
Xu *et al.* [167]	2017	85	—	—	—	—	—	—	—	—	—	—	—
Wu *et al.* [196]	2017	96.7	—	—	—	—	—	—	—	—	—	—	—
Deng *et al.* [25]	2017	100	100	100	98	95	88	85	98	100	92	82	79
Ma *et al.* [82]	2017	91	94	81	45	41	40	38	91	86	64	64	39
Atta *et al.* [140]	2017	92	91	81	42	35	21	25	87	80	63	9	6
Chaurasia *et al.* [143]	2017	90	89	84	38	42	22	28	90	80	72	20	18
Chhatrala *et al.* [86]	2017	100	96	91	72	70	50	45	85	93	91	40	40

Table 8 Accuracy on CASIA and OU-ISIR dataset B in per cent

		CASIA NL	CASIA BG	CASIA CL	OU-ISIR
Wang *et al.* [45]	2003	77.4	—	—	—
Yu *et al.* [3]	2006	97.60	32.70	52.00	—
Han and Bhanu [4]	2006	99.60	57.20	23.80	—
Bashir *et al.* [98]	2008	99.40	79.90	31.30	—
Rida *et al.* [118]	2009	97.50	83.60	48.80	—
Shanableh *et al.* [119]	2009	—	—	—	66.94
Bashir *et al.* [120]	2010	100.00	78.30	44.00	—
Hossain *et al.* [87]	2010	—	—	—	63.90
Goffredo *et al.* [180]	2010	86.50	—	—	—
Li *et al.* [88]	2010	99.20	80.60	75.80	—
Zhang *et al.* [123]	2010	98.39	91.94	72.18	—
Lu and Tan [169]	2010	100	—	—	—
Wang *et al.* [122]	2012	88.06	43.67	42.98	—
Huang and Boulgouris [127]	2012	99.00	64.00	72.00	—
Dupuis *et al.* [99]	2013	98.80	73.80	63.70	—
Jeevan *et al.* [128]	2013	93.36	56.12	22.44	—
Hu *et al.* [148]	2013	94.00	45.20	42.90	—
Islam *et al.* [95]	2013	—	—	—	78.54
Lee *et al.* [53]	2013	62.03	—	—	—
Kusakunniran *et al.* [181]	2013	98.00	—	—	—
Zeng *et al.* [21]	2014	91.9	—	—	—
Zeng and Wang [49]	2014	98.40	93.50	90.30	—
Kusakunniran *et al.* [131]	2014	95.40	60.90	52.00	—
Kusakunniran *et al.* [132]	2014	94.50	60.90	58.50	67.00
Lishani *et al.* [75]	2014	88.70	76.90	83.30	—
Rida *et al.* [100]	2014	95.97	79.03	80.65	—
Lee *et al.* [130]	2014	89.50	—	—	—
Lee *et al.* [137]	2014	89.50	—	—	—
Rida *et al.* [101]	2015	95.97	63.39	72.77	—
Rida *et al.* [113]	2015	95.56	74.11	86.61	—
Rokanujjaman *et al.* [102]	2015	97.61	83.87	51.61	72.90
Choudhury and Tjahjadi [89]	2015	100.00	89.00	76.00	—
Arora and Srivastava [133]	2015	98.00	—	—	—
Lee *et al.* [136]	2015	96.00	—	—	—
Luo *et al.* [134]	2015	88.70	89.90	91.90	—
Guan *et al.* [76]	2015	—	—	—	90.70
Arora *et al.* [138]	2015	98.00	74.50	45.00	61.20
Whytock *et al.* [103]	2015	98.40	77.40	93.10	—
Arora *et al.* [150]	2015	—	—	—	62.50
Rida *et al.* [104]	2016	93.60	81.70	68.80	—
Chhatrala and Jadhav [144]	2016	100.00	72.10	40.80	—
Deng *et al.* [54]	2016	94.00	93.00	92.00	—
Rida *et al.* [105]	2016	98.39	75.89	91.96	—
Rida *et al.* [78]	2016	98.80	70.10	89.29	—
Lishani *et al.* [79]	2016	93.55	87.63	89.24	—
Lu *et al.* [190]	2016	—	92.00	93.00	—
Nandy *et al.* [96]	2016	—	—	—	83.30
Liang *et al.* [111]	2016	99.6	94.76	91.53	—
Alotaibi *et al.* [108]	2016	98.40	86.70	94.80	53.70
Yeoh *et al.* [23]	2017	83.70	70.60	76.00	—
Deng *al.* [25]	2017	96.00	94.00	92.00	—
Verlekar *et al.* [90]	2017	100.00	87.00	96.00	—
Aggarwal and Vishwakarma [91]	2017	100.00	93.10	81.30	72.70
Lishani *et al.* [97]	2017	85.36	79.90	74.74	—
Alotaibi and Mahmood [107]	2017	98.40	86.70	94.80	—
Isaac *et al.* [109]	2017	98.00	95.50	93.00	—
Al Tayyan *et al.* [135]	2017	99.60	97.58	91.93	60.84
Atta *et al.* [140]	2017	98.00	73.00	66.0	—
Chaurasia *et al.* [143]	2017	98.40	88.70	58.90	—
Tang *et al.* [189]	2017	—	96.30	95.20	—
Ghebleh and Ebrahimi [110]	2017	—	—	—	82.13

Table 9 Clothing combinations

	Experiments																												
	3	**4**	**6**	**7**	**8**	**C**	**X**	**Y**	**N**	**S**	**V**	**0**	**2**	**5**	**9**	**A**	**B**	**D**	**E**	**P**	**T**	**Z**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**R**	**U**
S_1	RP	RP	RP	RP	RP	RP	RP	RP	SP	Sk	Sk	CP	RP	RP	RP	RP	RP	CP	CP	SP	Sk	SP	CP	CP	CP	BP	BP	BP	BP	BP	RC	Sk
S_2	HS	HS	LC	LC	LC	DJ	FS	FS	HS	HS	Dj	CW	HS	LC	FS	Pk	Dj	HS	LC	Pk	FS	FS	CP	CP	CP	BP	BP	BP	BP	BP	RC	Sk
S_3	Ht	Cs	Mf	Ht	Cs	Mf	Ht	Cs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

S_i stands for ith clothes slot. RP: Regular pants, BP: Baggy pants, SP: Short pants, Sk: Skirt, CP: Casual pants, HS: Half shirt, FS: Full shirt, LC: Long coat, Pk: Parker, DJ: Down jacket, CW: Casual wear, RC: Rain coat, Ht: Hat, Cs: Casquette cap, Mf: Muffler.

Table 10 Experiments in lateral view on CMU MoBo dataset

	Experiments											
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
gallery	slow	slow	slow	fast	fast	fast	inclined	inclined	inclined	ball	ball	ball
probe	fast	ball	inclined	slow	ball	inclined	slow	fast	ball	slow	fast	inclined

Table 11 Accuracy on the CMU MoBo database in per cent

	Experiments												
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	
Lee and Grimson [26]	2002	64	50	—	—	—	—	—	—	—	—	—	—
Wang *et al.* [45]	2003	36	—	—	48	—	—	—	—	—	—	—	—
Benabdelkader *et al.* [59]	2004	54	—	—	32	—	—	—	—	—	—	—	—
Liu *et al.* [35]	2004	72	88	—	—	—	—	—	—	—	—	—	—
Veeraraghavan *et al.* [207]	2004	80	48	—	84	48	—	—	—	—	68	48	—
Veeraraghavan *et al.* [208]	2005	80	48	—	84	48	—	—	—	—	68	48	—
Lee *et al.* [47]	2007	82	77	—	80	61	—	—	—	—	89	73	—
Kusakunniran *et al.* [209]	2009	92	73	—	92	61	—	—	—	—	75	63	—
Zhang *et al.* [123]	2010	72	—	—	44	—	—	—	—	—	—	—	—
Lam *et al.* [124]	2011	80	—	—	72	—	—	—	—	—	—	—	—
Choudhury and Tjahjadi [52]	2012	94	93	—	91	84	—	—	—	—	82	82	—
Roy *et al.* [125]	2012	100	92	60	88	60	72	76	80	48	92	84	76
Huang and Boulgouris [127]	2012	—	—	—	92	—	—	—	—	—	—	—	—
Choudhury and Tjahjadi [52]	2012	94	93	—	91	84	—	—	—	—	82	82	—
Wang *et al.* [122]	2012	72	—	—	76	—	—	—	—	—	—	—	—
Choudhury and Tjahjadi [48]	2013	96	92	—	96	92	—	—	—	—	92	87	—
Lee *et al.* [53]	2013	60	—	—	68	—	—	—	—	—	—	—	—
Zeng *et al.* [49]	2014	96	87	—	92	88	—	—	—	—	87	88	—
Kusakunniran [132]	2014	—	—	88	92	84	—	—	—	—	—	—	—
Huang *et al.* [210]	2014	93.36	65.71	47.81	—	—	—	—	—	—	—	—	—
Lee *et al.* [137]	2014	—	—	—	80	—	—	—	—	—	—	—	—
Lee *et al.* [130]	2014	80	—	—	88	—	—	—	—	—	—	—	—
Lee *et al.* [136]	2015	96	—	—	—	—	—	—	—	—	—	—	—
Huang *et al.* [211]	2015	96	—	—	96	—	—	—	—	—	—	—	—
Zeng et Wang [182]	2016	92	—	—	—	—	—	—	—	—	—	—	—
Deng *et al.* [54]	2016	—	99	—	97	98	—	—	—	—	—	—	—
Luo *et al.* [190]	2016	96	94	88	92	93	88	91	88	86	92	91	86
Wolf *et al.* [197]	2016	99	100	—	99	100	—	—	—	—	100	100	—
Kusakunniran *et al.* [212]	2012	92	—	—	88	—	—	—	—	—	—	—	—
Tang *et al.* [189]	2017	100	94	92	96	93	94	93	94	91	93	91	92

Hand-crafted or engineering features and especially GEI have been widely used and have shown attractive recognition performances in some specific scenarios, however, they fail in more complicated and unseen ones. Metric learning methods have shown their efficiency where the learned metric aims to find the appropriate distance which allows for the minimisation and maximisation of the intra-class and inter-class variations, respectively. Another way to address the aforementioned issues is to resort to domain adaptation with the objective to design a recognition method based on some training samples while the testing process is carried out using data with different statistical and geometrical properties (transport technique can be adapted to this application problem).

Finally, deep learning techniques have emerged as a new powerful research approach for gait recognition and have shown an attractive practicality in various application domains thanks to their impressive results. To be effective, such type of methods require a vast amount of labelled data in order to train the deep network architectures. Unfortunately, this is not the case of gait recognition where the existing datasets remain relatively of small size. A possible solution to tackle this problem is data augmentation and transfer learning techniques.

7 Conclusion

Gait recognition suffers from various intra-class variations caused by different conditions which drastically affect the recognition performances. In this paper, we have presented a comprehensive study of existing state-of-the art techniques for robust gait recognition dealing with clothing and view angle covariates. This is carried out by introducing simple and clear taxonomies, comparisons, summaries, and discussions of state-of-the-art recognition methods and algorithms in terms of the recognition performances using several widely used and publicly available datasets.

A large variety of hand-crafted features are related to the human expertise including the widely used GEI approach which offers different degree of robustness against intra-class variations caused by different conditions. These engineering features have shown good accuracy in some limited scenarios while failing when applied to more complicated ones. In order to attain superior recognition performances, feature representation and selection techniques have been combined with different features. A growing and intensive body of research, with the goal of end-to-end recognition from feature extraction and representation and classification, has emerged using the concept of deep learning. To be effective deep models require a huge amount of data, due to their complex structure coupled with their computing power to exhibit striking performances. Unfortunately, this is not the case for gait recognition problems due the limited size of existing datasets. To tackle this problem, data augmentation and transfer learning techniques are possible solutions.

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