

A Comprehensive Survey on Deep Gait Recognition: Algorithms, Datasets and Challenges

Chuanfu Shen, Shiqi Yu, *Member, IEEE*, Jilong Wang, George Q. Huang and Liang Wang, *Fellow, IEEE*

Abstract

Gait recognition aims at identifying a person at a distance through visual cameras. With the emergence of deep learning, significant advancements in gait recognition have achieved inspiring success in many scenarios by utilizing deep learning techniques. Nevertheless, the increasing need for video surveillance introduces more challenges, including robust recognition under various variances, modeling motion information in gait sequences, unfair performance comparison due to protocol variances, biometrics security, and privacy prevention. This paper provides a comprehensive survey of deep learning for gait recognition. We first present the odyssey of gait recognition from traditional algorithms to deep models, providing explicit knowledge of the whole workflow of a gait recognition system. Then deep learning for gait recognition is discussed from the perspective of deep representations and architecture with an in-depth summary. Specifically, deep gait representations are categorized into static and dynamic features, while deep architectures include single-stream and multi-stream architecture. Following our proposed taxonomy with novelty, it can be beneficial for providing inspiration and promoting the perception of deep gait recognition. Besides, we also present a comprehensive summary of all vision-based gait datasets and the performance analysis. Finally, the article discusses some open issues with significant potential prospects.

Index Terms

Gait recognition, deep learning, representation learning, biometrics security and privacy.

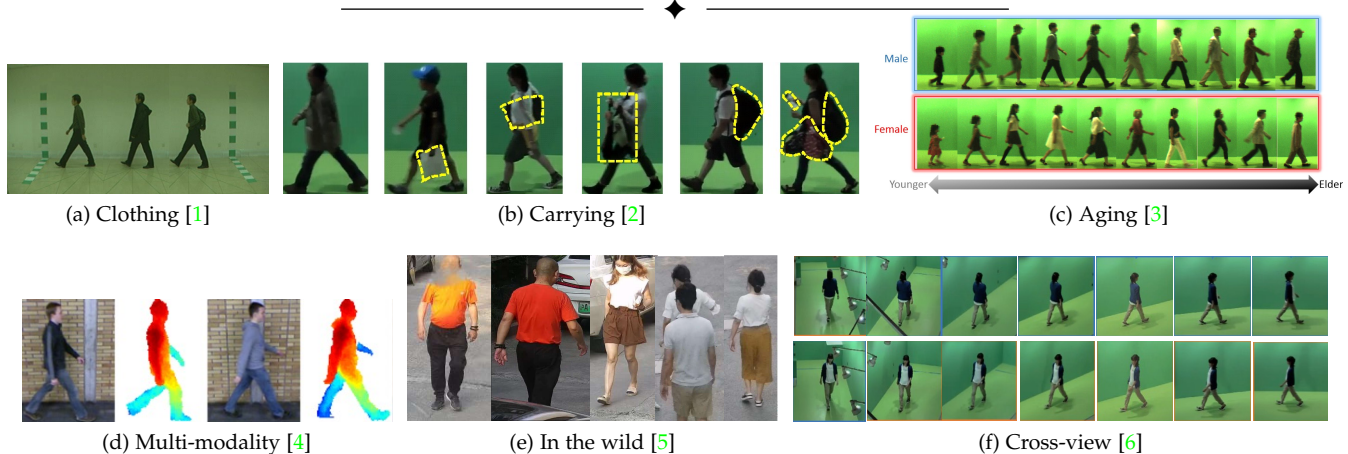


Fig. 1: Challenges and visual examples of gait recognition.

1 INTRODUCTION

Gait recognition is a biometrics application that aims to identify pedestrians by their walking patterns [27], [28]. In this paper, we refer gait recognition as a vision-based person

Chuanfu Shen is with the Department of Computer Science and Engineering, Southern University of Science and Technology, China, and also with Department of Industrial and Manufacturing Systems Engineering, The University of Hong Kong.

Shiqi Yu is with the Department of Computer Science and Engineering, Southern University of Science and Technology, China.

Jilong Wang is with the University of Science and Technology of China and also with Center for Research on Intelligent Perception and Computing (CRIPAC), Institute of Automation, Chinese Academy of Sciences.

George Q. Huang is with Department of Industrial and Manufacturing Systems Engineering, The University of Hong Kong.

Liang Wang is with the Institute of Automation, Chinese Academy of Sciences. Corresponding author: Shiqi Yu, E-mail: yusq@sustech.edu.cn

retrieval problem that is to identify the moving subjects of given gait sequences captured from visual cameras. The outstanding advantage of gait as a biometric is that it is feasible for human identification at a distance [29]. In other words, gait can be utilized at low resolution. Gait describes spatial statics and temporal dynamics in human motion. It typically occupies much more pixels than other biometrics (*e.g.*, face, fingerprints, iris), empowering human identification at a distance by gait. Moreover, an alternative advantage of gait to recognize the subjects is that it requires less cooperation, while other biometrics heavily rely on active cooperation. Due to invalid surveillance systems during the COVID-19 pandemic [30], gait recognition has shown superiority in such situations. It has received increasing expectations for ensuring our public security shortly.

Albeit the research on gait recognition shortly start-up three decades ago [28], [31], the achievements since then

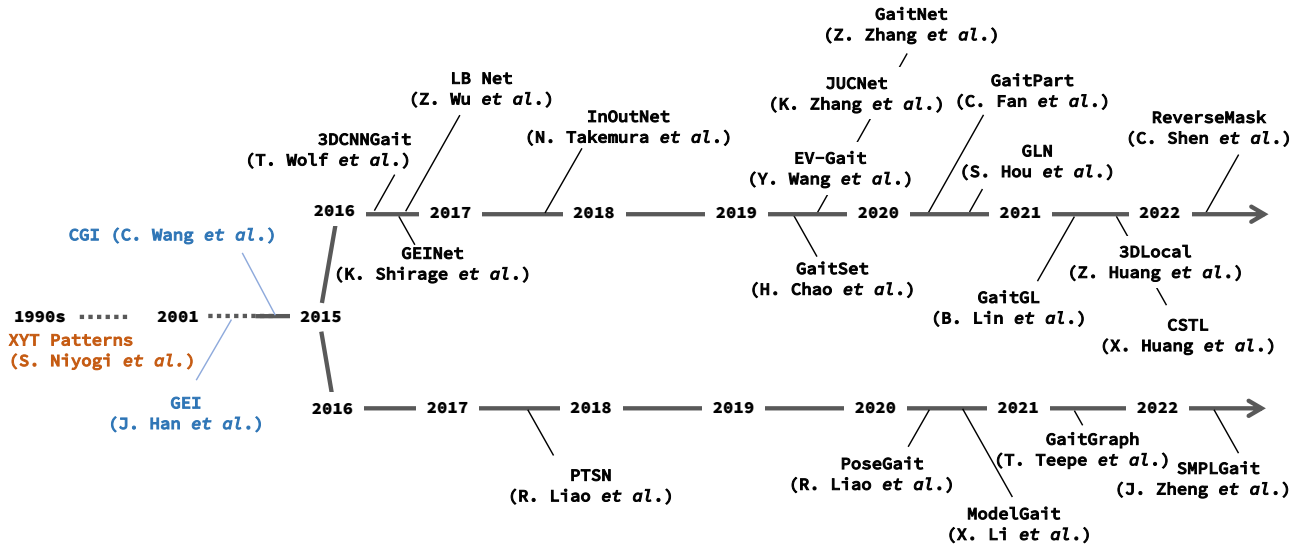


Fig. 2: Milestone of gait recognition approaches. The reference in orange represents methods at the early stage, while references in blue indicates handcrafted feature-based methods. The references in black are representative works in deep learning era. We categorise appearance-based methods 3DCNNGait [7], GEINet [8], LBNet [9], InOutNet [10], GaitSet [11], [12], EV-Gait [13], JUCNet [14], GaitNet [15], GaitPart [16], GLN [17], GaitGL [18], 3DLocal [19], CSTL [20], ReverseMask [21] on the top branch. The bottom branch presents some representative model-based methods, such as PoseGait [22], PTSN [23], ModelGait [24], GaitGraph [25], and SMPLGait [26].

have continued to promote and extend the field of gait study. The research on recognition by gait can be divided into three stages from our best knowledge. The earliest stage started in the early 1990s [31] and mainly aimed to explore the feasibility of human identification at a distance. The contemporary approaches to gait achieved reasonable performance but were only evaluated on small-scale benchmarks [27], [32] which contain ten subjects at most.

Later on, the following second stage derived from DARPA released Human ID at a Distance (HumanID) [33], [34], [35] program, promoting not only techniques but also datasets. Many template-based approaches [36], [37], [38] can be distinguished as the mainstream techniques for automatic recognition. At the same time, an alternative category of approaches used coarse human-model techniques [39], [40], [41] to represent structural and dynamic features of pedestrians. The construction of datasets started to consider over a hundred subjects [1], [42], [43] and investigated several important factors, such as view variants [27], [44], and appearance-changing [1], [29]. With such promising evaluation performance and sufficient evidence of feasibility, it revealed that gait recognition is feasible and has potential for further exploration.

Then the research of gait recognition stepped into the deep learning era. The recognition approaches in the deep era can capture complex motion features directly from sequential inputs [12], [16], [18], [20], [45], and such methods dramatically outperform conventional approaches based on hand-crafted features like many template-based methods (e.g., gait energy images [36], gait history images [46]). With the emergence of deep learning techniques, gait recognition has achieved inspiring performance on many widely used benchmarks. Besides, the research of deep era is toward gait recognition in more complex scenarios, such

as recognition in a dataset containing over ten thousand subjects and robust recognition in the wild (as illustrated in Fig. 1).

There is significant improvements on recognition performance with the major contributions of deep learning techniques, and these performances on mostly used benchmarks can explain the feasibility of gait recognition as a powerful tools for public safety. Within deep gait recognition era, the overall recognition accuracy is beyond 93% [21] under very difficult appearance-changing setting on CASIA-B [1]. Of the study recognition on a larger participants, more than 10 thousand subjects were sent to deep gait models, gaining 97.5% [21] rank-1 accuracy on OUMVLP [6] dataset. In response to issue under outdoor setting, GREW [5] and Gait3D [26] were to explore large-scale gait recognition in the wild, while Gait3D also provided extra 3D annotation to study model-based applications. Besides, the surprising results of the HID2022 [47] competition even exceeded 95.9% on the setting with pedestrians sometimes stopping and looking around.

The above achievements of deep gait recognition with great significance motivated us to come up with this survey of deep learning for gait recognition. Although there are many surveys [48], [49] covering some contents of deep learning, our survey fills the gap by reviewing the latest methods in the deep era, summarising network architectures, revealing what components of the models contribute to performance, and analyzing gait representations comprehensively. Specifically, the significant contributions of this survey are as follows:

- We provide a complete and comprehensive survey on deep gait recognition and cover the most recent and advanced progress of deep learning on gait recognition.

- We analyze the current deep gait recognition methods from different aspects, including input data, feature representation learning, metric learning, and network architecture. Fruitful reviews on each aspect are given to guide future research.
- Attempting to address the future of gait recognition, we make relatively long content on datasets, method evaluation, security, and privacy concerns. Those are important aspects for the next stage of gait recognition.
- We also describe the challenges in gait recognition and give our suggestions on future directions based on the analysis of the past decade’s progress.

The rest of the survey is organized as follows. We first introduce an overview of gait recognition and typical pipelines of gait recognition systems in Section 2. Section 3 reviewed different methods to learn deep representations and metric learning methods used in gait recognition. Section 4 presents the deep network architectures for gait recognition. Datasets and evaluation methods are reviewed in Section 5. The security and privacy concerns are introduced in Section 6, followed by challenges and suggested directions in Section 7. The last section concludes the paper.

2 OVERVIEW OF GAIT RECOGNITION

Before a detailed introduction to different deep algorithms for gait recognition, we first present an overview of gait recognition systems in this section. The overview contains input data, handcrafted features, deep features, matching, and post-processing. The odyssey of the development from step-by-step to end-to-end is also introduced.

2.1 Different Kinds of Input Data

Many kinds of input data from different sensors can be used for gait recognition. RGB images captured from cameras are the most commonly used modality because they are simple and low-cost to install. However, the traditional RGB-Cam fails to work under inadequate illumination. Then near infra-red cameras with active infra-red lights are used for gait recognition [43] at night. Unlike infra-red images, thermal images from thermographic cameras do not need active illumination for imaging and can also be used for gait recognition [50]. Nevertheless, the contours of a human body in a thermal image are blurred, which is lower quality than visible light or near-infrared images. Depth images can provide contours of more accuracy and incremental three-dimensional information. Therefore some works are based on depth images [51], [52]. However, such depth sensors only work indoors or under conditions of little sunlight. Besides, the motion data and pressure data from some wearable sensors [53], [54] and pressure sensors [55] can also be used for gait recognition. This paper focuses on vision-based gait recognition, and gait data extracted from visual sensors are introduced specifically in this paper. Different kinds of visual data are presented in Figure 3 as follows.

RGB Image. RGB images contain much information to identify different subjects. However, the texture and clothing biases [56] are introduced when learning algorithms apply directly to RGB images. If RGB images are rarely

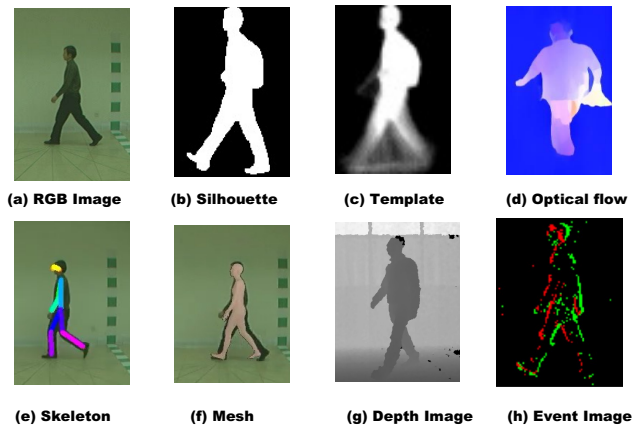


Fig. 3: Different kinds of data for gait recognition.

taken as the input directly, the algorithm will recognize different subjects according to their appearance and walking styles [57]. In gait recognition, the clothing is regarded as a kind of variation, and gait recognition should be robust to different clothing styles. Many recent methods [15], [24] take RGB images as input, extracting representations robust to clothing and texture and achieving outstanding results. We believe that RGB images have great potential for gait recognition since rich information has not been fully utilized.

Silhouette. A silhouette is the human body mask by removing the background. Human silhouettes were primarily obtained by background subtraction at an early age. At the same time, the advanced segmentation methods based on deep learning can provide much better quality human silhouettes than background subtraction. Human body silhouettes still contain an informative appearance even if it removes color and texture, but internal body structure information is partially lost in silhouettes. Silhouettes are easy to be affected by clothing and the camera views [58]. Since its efficiency and simplicity, silhouettes were the most popular gait data in the past 20 years [11], [16], [59], [60], [61], [62].

Gait Template. Although silhouettes are efficient and simple, a sequence of silhouettes is high-dimensional. Before deep learning was widely deployed for visual recognition, it was not easy to extract features from sequential silhouettes using traditional methods like SVM [63], [64] and Boosting [65]. Han *et al.* [36] proposed Gait Energy Image (GEI), in which average cyclic silhouettes sequence into a single gait template, and such denoising processing aims to be robust for incomplete silhouettes. GEI contains comparable information to sequential silhouettes, and its data dimensionality is much less. Despite its simplicity, GEI is robust to many variations and achieved great success in gait recognition. Besides GEI, some other similar features have also been proposed. They are Motion Energy Image (MEI) [38], Gait History Image (GHI) [38], Gait Entropy Image [66], Chrono-gait image (CGI) [37], Gait Moment Image (GMI) [67], *etc.* Even though deep models can handle the high data dimensionality of sequential silhouettes, some recent methods [8], [68] still prefer using GEI because of its low computational cost and robustness on noise.

Optical Flow Image. Gait recognition is a task to identify

a subject via its walking patterns. The motion information is significant but hardly described from silhouettes. Therefore Optical flow images are utilized to provide more motion information than silhouettes. Castro *et al.* also demonstrates that optical flow images can achieve state-of-the-art performance [69]. However, the computational cost for optical flow images is relatively high, and it is also very challenging to obtain optical flow images of high quality. Recent deep learning-based FlowNet [70] and its successors [71], [72], can achieve relatively better optical flow images and might improve gait recognition accordingly.

Body Skeleton. Many methods of the early stage, employ body structures to extract gait patterns [39], [40], [41]. The gait recognition methods based on skeleton should be more robust to view and clothing variations than those based on silhouettes. However, it is not easy to extract high-accuracy human body models at the moment. Human pose estimation has achieved encouraging precision via deep learning in recent years. Those human pose estimation methods include but not limit to DeepPose [73], OpenPose [74] and HR-Net [75]. Then gait recognition with human body models have returned back research of interest [23], [25], and many datasets [5], [76] with pose annotations presented to advance model-based gait recognition.

Human Mesh. Mesh is a type of 3D representation that consists of a collection of vertices and polygons to define the exact shape of an object [77]. There are various human mesh recovery methods [78], [79] to construct a complete 3D body model, and human mesh can provide more structural information than skeletons. ModelGait [24] fine-tunes a mesh recovery model on a gait dataset and distinguishes different subjects via extracted structural parameters, showing the promising performance of utilizing human mesh as auxiliary supervision information. Gait recognition based on body meshes will be an exciting topic in the future with the improvement of human body mesh estimation accuracy.

Depth Image. Unlike color images, depth images can provide a 3D structure of bodies since each pixel value is the distance between the object and the camera. The low-priced depth cameras like Kinect [80] provide the possibility for gait recognition using depth images. In [4] traditional GEI is compared with depth-based templates such as Depth-GEI, DGHEI, and GEV, and experiments show that depth templates can achieve better performance. A complete review on gait recognition with depth images can be found in [81] which provides a public depth datasets and introduces most methods with depth images. Depth image-based gait recognition has a primary challenge in that a depth camera can only capture data in a range of 10 meters. Besides, the active infrared light from depth cameras will decrease dramatically with the distance and can also be disturbed by sunlight. For those reasons, gait recognition with depth images is difficult to deploy into an outdoor system to capture gait from a distance.

Dynamic Event Stream. Other advanced cameras, event stream cameras, can capture high-speed movements without blurs. The dynamic vision sensors can capture microsecond-level pixel intensity changes as events by a class of neuromorphic devices. Therefore, the event stream is converted into image-like representations, allowing CNN-based methods to extract discriminative features. Event

streams may provide much more promising performance from their ability to capture high dynamic fine-grained motion. EV-Gait [13] is the first work we find in the literature on dynamic vision sensors for gait recognition. It achieved nearly 96% recognition accuracy in a real-world setting and comparable performance with state-of-the-art RGB-based gait recognition methods on the CASIA-B benchmark. However, more studies on this new sensor are needed, and it is great potential for event cameras to deploy gait recognition systems in the future.

2.2 Handcrafted Feature Extraction

Gait recognition methods before the deep era are generally grouped into two categories: model-based methods based on the construction of human models and appearance-based methods based on appearance features.

The human body models in model-based methods can also be divided into structural and motion models. The *structural* models [82], [83] employ the static body parameters such as stride length and cadence as clues. For example, Boulgouris *et al.* [84] uses labeled structural gait silhouettes and extracts component-wise discriminant representations to recognize different subjects. The alternative *motion* model-based approaches exploit dynamic motion features for gait recognition. The phase-weighted magnitude spectra are in an early attempt [85]. Another similar method [28] employs Fourier description from the motion of the hip and thigh. There were also some works trying to combine static body structure and dynamic motion to improve the accuracy [86].

The **appearance-based** methods use the source of input directly without constructing human models. The appearance-based methods dominate gait recognition because of their effectiveness and efficiency. In 2002, Shi [87] proposed a viewpoint-dependent silhouette-based baseline method and extracted keyframes for further matching. Wang [88] applied principal component analysis (PCA) to reduce the dimensionality of the input feature since the original silhouettes are in a high dimension space. Because many gait templates [36], [66], [67] were experimentally proved effective, the majority of gait recognition methods migrated to use gait templates as gait features even in the deep learning era.

2.3 Deep Feature Extraction

With the significant progress of deep learning, hand-crafted engineering transforms into automatically deep architecture engineering. As illustrated in Figure 4, the early deep gait recognition methods [8], [9] combine feature learning and classification and replace them with deep feature learning. However, such early attempts are not paying much attention to temporal information extraction among gait sequences since they heavily rely on gait template [36], [37]. The template-based gait recognition is more likely to be an image classification task than a video-level recognition task. Later on, many works [61], [89] extracts features directly from a sequence of silhouettes, and frame-level features can be extracted from a sequence. Albeit deep gait recognition methods with silhouettes have achieved satisfying performance, they still have many limitations, such as neglecting

overlapped body parts and requiring accurate foreground segmentation.

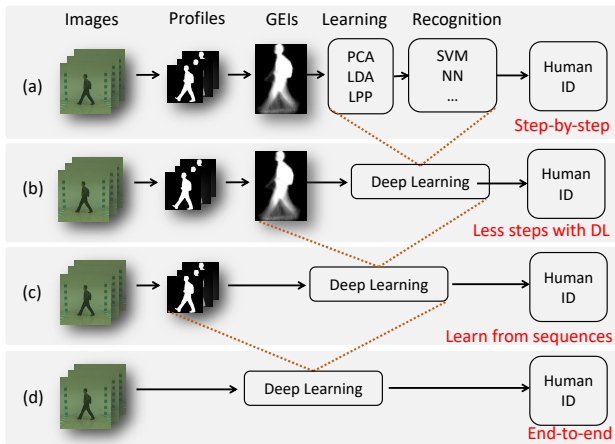


Fig. 4: Four typical workflows on deep gait recognition. [61]

2.4 End-to-End Gait Recognition

There are many steps in gait recognition, especially when handcrafted features are employed. As show in Figure 4.(a), there are data pre-processing, feature extraction, classification, and other steps. In deep pipelines of gait recognition, fewer steps are needed since deep models have the capability of both representation learning and classification. However, there are still several steps, as shown in Figure 4.(b). Recently deep gait recognition tends to be implemented in end-to-end manners [24], [57], [90]. Learning from RGB frames can capture rich information from a holistic body and optimize all steps in an end-to-end manner.

Song *et al.* tried to use an end-to-end solution in their proposed GaitNet [61] which integrates the process of recognition and silhouette segmentation in a single step by a deep net. The achievement made by end-to-end recognition is remarkable, and this solution was effective. Another end-to-end work [24] tries jointly recover human 3D models and extract gait features for recognition. The philosophy of end-to-end recognition is straightforward, endowing the learning algorithms with automatic perception for gait representations.

2.5 Matching and Post-processing

Verification and identification are two modes in biometrics. The difference is that verification is the one-to-one comparison, and identification is the one-to-many comparison [91]. In a verification scenario, a subject will present his/her face or fingerprint to a sensor and an ID card to claim their identity. Unlike face or fingerprint, gait is seldom used in a verification scenario. In the literature [29], [92], gait recognition methods typically are evaluated in an identification mode. Identification mode is when samples from the probe sets are taken out to compare with the samples in the gallery set. Noticed that biometrics recognition systems can typically be separated into two kinds of classification problems: open-set classification or closed-set classification detailed in [91].

The most commonly used metric is L2 distance in comparisons. Other distances such as cosine distance can also be employed [93]. As a retrieval task, many post-processing methods such as ranking optimization can be used to improve recognition accuracy. In HID2021 competition [94], most participants achieved top performance all used re-ranking [95]. It shows that re-ranking can improve accuracy.

3 DEEP REPRESENTATIONS LEARNING

Representation learning and metric learning are the primary core of deep gait recognition. Specifically, representation learning extracts abstract representations from multi-layer deep networks to describe gait data. The objective of metric learning is to learn feature space for learned representation by distance constraints or modeling the distribution of samples. To extract discriminative features to distinguish different subjects is harsh because it tends to have high intra-class and low inter-class variance for gait. We analyzed them in different dimensions in the following part of this section.

3.1 Feature Representation Learning

Gait can be considered as a combination of static parameters and dynamic motions. So representation learning can be carried out from two perspectives: *i)* static feature representation learning for extraction of spatial information such as height, body shape, etc. *ii)* dynamic feature representation learning by modeling of motions to capture different human motion patterns.

3.1.1 Static representation learning

Figure 5 shows many kinds of static gait features. Gait representation can be learned from different aspects, global and local representation learning, 2D and 3D representation learning, and single-scale and multi-scale representation learning. In this subsection, static representation learning only considers those static representation learning related to spatial information.

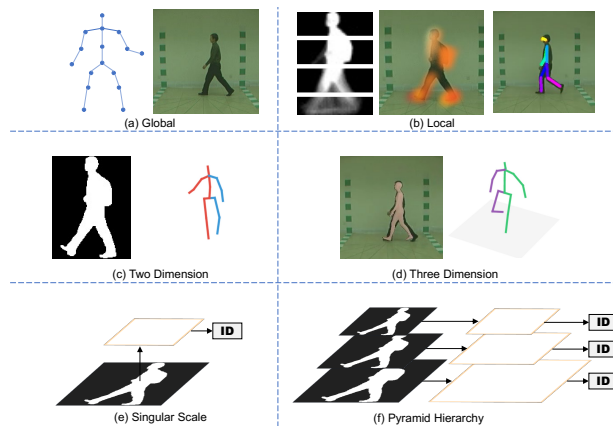


Fig. 5: Different kinds of static representation learning.

(a) Global/local representation learning

Global feature representation learning considers the human body as a whole to extract features. It is straightforward to capture holistic representations from gait data, such as

silhouettes, into CNN networks for gait recognition. Many early gait recognition methods based on deep learning use global representation learning. Hossain and Chetty introduced deep learning into gait recognition, used several layers of convolution to extract the whole GEI templates [96], and demonstrated the significant improvement from the fusion of deep features. Similar methods can also be found in [8], [9]. Differently, GaitSet [11] takes silhouettes nor GEI as input and uses six convolutional layers to extract global spatial features. Global representation can also be learned from human body parameters such as body joints estimated from images by OpenPose [74] or similar methods. This human body joints can also be taken as a whole and input into a deep model as in [23], [97], [98] to extract global features. Global spatial static features, whether appearance-based or model-based, are easy to use but not robust to appearance changes such as view and clothing.

Local feature representation learning is an alternative to learning fine-grained features by part-based methods, which attempt to learn spatial representations from the partial region of human bodies. Many recent works [18], [89] have indicated that methods based on local representation learning can achieve better results. In the early years, Liu *et al.* [99] point out that the different parts of the human body have various shapes and moving patterns. Recently, GaitPart [16] used focal convolution on different body parts and demonstrated that local representation could offer more fine-grained information for recognition. The most commonly used body part separation separates a body into horizontal strips as in [11], [16]. Moreover, local feature also can be extracted from pose-driven region of interest (RoI) [100], attention region of appearance [101], body component by parsing [99] or patch-level [102]. For model-based features, GCN [103] can be applied to learn joint local features by relation modeling of adjacent joints. Local representation learning has gained increasing interest in recent years, but it still needs more research to advance gait recognition.

In conclusion, global features pay more attention to the information in holistic, whereas local features focus on partial information. Global features contain more coarse information, while local features contain fine-grained information. Some recent attempts [11], [18] combine the two kinds of features for better performances, which is a reasonable solution for learning better representations.

(b) 2D/3D Representation Learning

2D representation learning is a category of methods that extract 2D geometric information from data captured by 2D visual sensors. As shown in figure 5(c), the 2D representation methods can extract spatial features from 2D images or skeletons. Because of its simplicity and efficiency, 2D representation learning dominates gait recognition and has been the mainstream representation during the past two decades. Wu *et al.* [9] proposed a milestone method that employed GEI and CNN for gait recognition and provided detailed experiments to show that deep learning can boost gait recognition significantly. Many other methods also belong to 2D representation learning, such as GaitSet [11] and GaitPart [16]. Wang *et al.* [13] introduced event cameras into gait recognition. The event stream representation from event cameras can remove noise effectively by motion consistency, and it provided a promising result compared with RGB-

based gait recognition approaches. 2D representation learning is also involved in it. In addition, some model-based methods [23], [25] also use 2D skeleton, utilizing structural information to optimize deep models.

3D representation learning is to learn features from 3D human body data, which is captured from advanced sensors or estimated from 2D images. 3D representation is more robust in viewing changes than 2D representation. To estimate 3D models from images is challenging, especially in the early years. Therefore many researchers tried to capture the depth images of human bodies [4], [81], [104]. The primary issue of depth sensors is that depth cameras are only feasible indoors and incapable of being used when the distance to pedestrians is over 10 meters. In recent years, with the progress in human modeling from RGB images [74], [78], [79], many approaches attempting to estimate 3D human body models from RGB images [22], [24], have achieved promising performance.

(c) Single/multi-scale representation learning

Single-scale representation learning was the most popular technique at the early stage of study because it is easy to implement and has a low computational cost. Many recent methods still use such single-scale imagery for representation learning [8], [10], [105]. A typical example is GEINet [8] which takes GEIs as input and extracts deep features for recognition, as implemented in another similar learning method [9].

Multi-scale representation learning have been widely used in computer vision in both the deep learning era [106] and the era of the handcrafted feature. It can deal with multi-scale problems, objects ranging from many different scales. Multi-scale learning has been widely adopted in object detection, especially multi-scale detection. It is also popular in person re-identification [107], [108]. Multi-scale learning can enhance the discriminative capabilities of different human body parts. Increasing attention to multi-scale learning is also gained for gait recognition in recent years. For example, GaitSet [11] employs horizontal pyramid mapping to extract features from different sizes and positions, which is inspired by the works in [107], [109]. GLN [17] also utilized a hierarchy pyramid structure to learn robust representations. As the analysis in [106], the attention pyramid network works well in the tasks of fine-grained image classification. We think multi-scale learning is essential in gait recognition since discriminative features can be extracted at different scales.

3.1.2 Dynamic representation learning

The dynamic features can describe human motion, which perfectly matches the need for gait recognition, but extracting dynamic features is always challenging [22], [39]. Dynamic features (in Figure 6) are typically aggregated with some static features to achieve better accuracy. This section introduces dynamic representation learning methods for deep gait recognition from three aspects: template and frames-based, long and short term, and shuffled and ordered.

a) Template/frames-based representation learning

According to whether converting an entire gait sequence into a template such as GEI, temporal representation learning could be categorized into *template-based* methods and

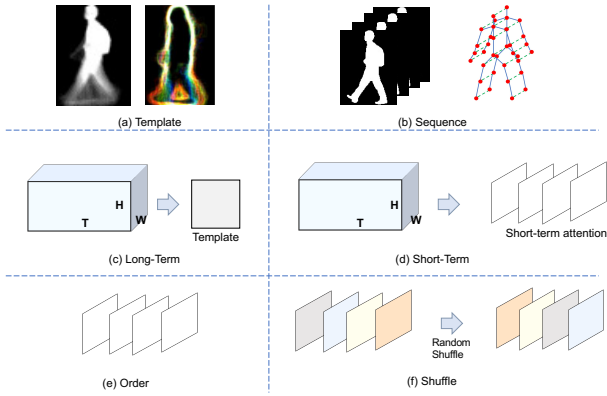


Fig. 6: Different kinds of temporal feature representation learning.

frames-based methods. Template-based methods usually fuse frames into one template image [36], [37], [38], [66]. It is commonly used before the deep learning era and in some early deep methods. In recent years, many methods have taken frames nor a template as input [11], [16], to extract dynamic gait information from a sequence of frames.

Most *Template-based* methods [36], [37], [66], [110] were widely proposed at early stage of gait recognition. Gait Energy Image (GEI) [36] is the most popular one for its low computational cost and temporal robustness. GEI represents the average of the cyclic silhouettes. The static information is primarily maintained, but gait motion information is partially lost within GEI. Template-based representation learning was popular in the past because most traditional learning methods such as SVM [63], [64], Boosting [65] cannot handle high dimensional data very well. Deep learning methods are superior to traditional learning methods on feature learning. Therefore many recent methods have moved to study frames-based representation to obtain dynamic motion features for better performance.

Frames-based methods take the frames as input, and most methods [20], [61], [111] use silhouettes. Some use body poses [25] or others [24], [26]. Adjacent frames within a gait sequence can describe explicit motion patterns. Various deep models have been employed for frame-based methods, capturing fine-grained and implicit temporal information. 2D/3D CNN [7], LSTM [112], GCN [103] *et al.* are commonly used. Temporal modeling is well investigated in the typical frames-based method, GaitSet [11], [12]. With the presence of set pooling, many successors extended temporal modeling to micro-motion modeling [16], long-short term modeling [60], and attentive modeling [20]. It is a trend that deep gait recognition takes advantage of sequential inputs to improve recognition robustness and accuracy.

(b) Long/short-term representation learning

Long-term representation learning tries to extract long-term temporal gait features. Song’s GaitNet [61] is a typical long-term representation learning method that takes all silhouettes and processes them in a temporal fusion unit. Most frames-based methods [11], [111] aggregating a whole sequence into a feature vector can also capture long-term temporal representations. In addition, template-based methods [36], [66] utilizing a long sequence into a single gait

template are also capable of maintaining partial dynamic information.

Short-term representation learning is to extract some short-term fine-grained motions rather than the global motion. A typical deep model is long short-term memory (LSTM) [113]. LSTM is a type of recursive neural network commonly used in the field of speech recognition and handwriting recognition for sequential signals. It is also widely used in gait recognition. PTSN [23] and Zhang’s GaitNet [114] use LSTM to capture short-term micro-motions. Besides, GaitPart [16] has a novel micro-motion capture module and a frame-level part feature extractor, which aim to enhance the ability to learn short-term fine-grained Spatio-temporal features. In conclusion, extracting discriminative short-time features is a still challenging topic with great potential for further investigation.

(c) Shuffled/ordered representation learning

Shuffled image sets as input are introduced in Vinyals *et al.*’s work [115], showing that good performance is guaranteed even if the input is unordered. The idea is also widely used in natural language processing, which was first introduced in GaitSet [11] for gait recognition. GaitSet shows that the input frames can be in shuffled sequences. It applies a Set Pooling (SP) module to aggregate features in the temporal dimension. Similarly, an SP module is also employed to aggregate features in [17]. The method in [116] steps even forward to a single frame for gait recognition. The advantage is that we do not need to align gait sequences in the temporal dimension when shuffled frames are taken as input. Those methods should be robust to noise since sequence alignment is not that easy when many variances and noises exist.

Ordered frames as the input seem to be a more straightforward idea for gait recognition since gait data can be regarded as time-series signals. Moreover, many gait recognition methods also take ordered frames as input and use some models in NLP, such as RNN, LSTM, and 3DCNN, for feature extraction. GaitPart [16], Song’s GaitNet [61] and MT3D [60] all take ordered frames as input and try to extract dynamic features among the frames by some temporal modeling module inside the deep networks. Similarly, GaitGL [18] also takes ordered frames for temporal feature extraction.

We think that the concept of GaitSet [11], [12] that order is not essential for gait is not accurate. From our views, robust gait representations can be extracted from shuffle sets only under uncontrolled setting [5], while many methods achieved better performance by utilizing ordered temporal representations if pedestrians walk continuously. It is because temporal features among frames are maybe not that easy to be extracted when pedestrians stop and walk with many micro-actions, such as picking up a cellphone or looking around. In conclusion, shuffled gait inputs provided a simple guide to model temporal representation in holistic, and fine-grained micromotion is much more potential to be captured from ordered inputs.

3.2 Deep Metric Learning

Loss functions are used to measure the errors of deep models and guide the back-propagation in model training.

Different tasks normally employ different losses. Some popular loss functions in other tasks have also been used in gait recognition.

3.2.1 Cross-entropy loss

Since gait recognition can be regarded as a classification task, cross-entropy loss, also known as softmax loss, has been used in gait recognition [8], [9]. Each subject is considered a separate class.

The optimization goal of cross-entropy loss is to make the probability distribution of the model output as close as possible to the ground-truth, the identification labels. The loss function is

$$L_{ce} = -\frac{1}{P \times K} \sum_{i=1}^{P \times K} \sum_{n=1}^N q_n^i \log(p_n^i),$$

Where N is the number of all identities in the training set, $P \times K$ denotes the number of samples in a mini-batch, p_n denotes the probabilities of sample i belonging to identity n , and q_n is a binary indicator (0 or 1), if $n = y$ then $q_n = 1$ (taking the y -th identity as an example).

However, the cross-entropy loss cannot fit gait recognition very well. In gait recognition, the number of classes may be huge. There are about 10,000 subjects in OUMVLP Dataset [6], and the number of samples for each class/subject is not large enough. Besides, the inter-class difference among different classes is significant.

3.2.2 Contrastive loss

Since cross-entropy loss cannot handle many classes well, another option is to employ pairwise losses. Contrastive loss is a typical one that forces the distance between positive pairs is less than the distance between negative pairs by at least a margin value.

$$L_{con} = \frac{1}{2N} \sum_{n=1}^N (y_n d_n^2 + (1 - y_n) \max(\text{margin} - d_n, 0)^2),$$

where N is the number of training sample pairs and d_n is the dissimilarity score (usually calculated by L2 norm distance or inner product) of the n -th pair. y_n is a binary indicator (0 or 1), setting to one when the samples in the n -th pair from same identity. The *margin* is a constant value.

3.2.3 Triplet loss

Triplet loss [117] is widely used in recent state-of-the-art methods [60], [60]. Instead of using pairs, this loss takes distance triplets (*anchor*, *positive*, *negative*) as input. The loss pulls the positive close to the anchor and pushes the negative away from the anchor. In order to prevent the features from converging into a small space, the distance between the anchor-negative pair should be at least one *margin* farther than that of the anchor-positive pair.

$$L_{tri} = \frac{1}{N_{tp+}} \sum_{\substack{a,p,n \\ y_a=y_p \neq y_n}} \max(\text{margin} + d(a,p) - d(a,n), 0),$$

where N_{tp+} denotes the number of triplets of non-zero loss terms in a mini-batch, a, p, n stand for anchor, positive and negative respectively. $d(a, p)$ and $d(a, n)$ denotes the distance between anchor-positive and anchor-negative respectively. The *margin* is a constant value.

3.2.4 Other losses

The losses mentioned above are mainly adopted from image classification, face recognition, or person re-identification. Although gait recognition has some similarities with these two tasks, the problem of the large intra-class difference in gait data, *e.g.*, cross-view and cross-walking-condition settings, has not been well considered. Aiming to solve the weak discriminative feature representation in cross-entropy loss and the lack of hard negative mining in contrastive loss and triplet loss, Zhang *et al.* [89] proposed a gait-related loss named Angle Center Loss (ACL). ACL is a view-specific hard mining center loss. Another loss, Quintuplet loss [14], is also designed specifically for gait recognition. Quintuplet loss simultaneously boosts inter-class differences by pushing different subjects further apart and contracts intra-class variations by pulling the same subjects closer.

4 DEEP GAIT ARCHITECTURES

In this section, we firstly introduce the typical components in deep gait recognition models as shown in Figure 7. Then, we also review the last works in the literature and categorize them into two architectures: single-stream and multi-stream architecture.

4.1 A Glimpse of Architectures for Deep Gait Recognition

Most gait recognition methods mainly consist of three components: a backbone for gait features extraction, a bottleneck for spatial-temporal feature aggregation, and a head for representation mapping.

4.1.1 Backbone networks

The term "Backbone" refers to the network which plays a role in the feature extractor, which typically encodes the input into a feature representation. There are many commonly used hand-crafted features such as gait templates [36], [66] and trajectories [118] in the traditional gait recognition literature. With the rise of deep learning, the learned features by various deep networks outperform previous feature extractors by a large margin.

The Convolutional Neural Networks (CNNs) [15], [105], [119] are the primary and seminal backbone networks among deep gait recognition models. Although some early works [9], [11] use 2D CNNs as backbones and demonstrate learned features are superior to learning discriminative features for gait recognition, the backbones with only 2D CNNs perform less effectiveness in capturing temporal information. Hence, Thomas *et al.* [7] introduced the advanced backbone consisting of a shacked 3D convolutional layers, trying to obtain robust Spatio-temporal features for better identification. Albeit the previous convolutional networks illustrated its satisfying performance and outperformed traditional manually engineering features, these backbone networks borrowed from other visual recognition tasks are not specifically designed for gait recognition. Then it inspired recent literature to explore gait-specific backbone networks such as focal convolutions [16], [18] proposed to capture fine-grained gait patterns from horizontally partitioned inputs, and 3D local convolutions [19] aimed to obtain part-specific information from the pedestrian body adaptively.

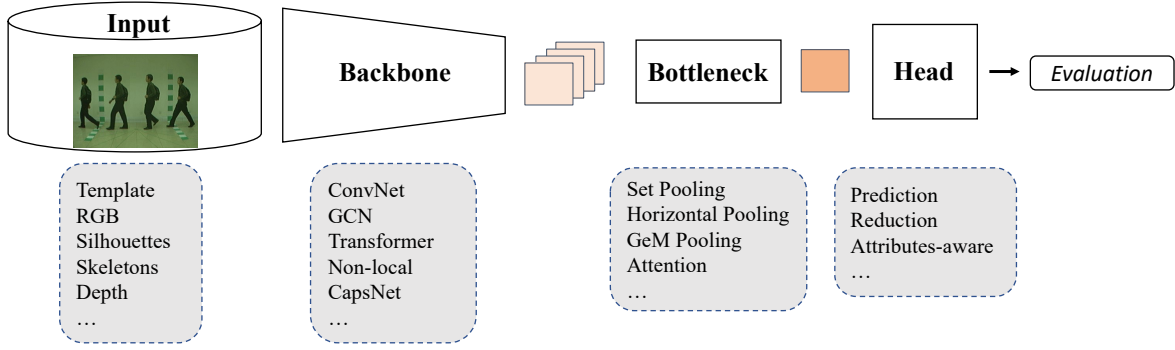


Fig. 7: The typical workflow of deep gait recognition models.

TABLE 1: The architecture of some recent representative works.

Method	Year	Backbone	Bottleneck	Head	CASIA-B	OUMVLP
GEINet [8]	2016	2D ConvNet	-	Identification	35.8%	42.5%
LB network [9]	2016	2D ConvNet	-	Verification	72.1%	-
JointCNN [111]	2019	2D ResConvNet	Temporal Average	Identification	73.4	-
Song GaitNet [61]	2019	2D ConvNet	Temporal Average	Identification	89.9 ^a	-
ACLGait [89]	2019	2D ConvNet	LSTM	-	96.0 ^a	89.0
EV-Gait [13]	2019	2D ResConvNet	-	Identification	89.9 ^a	-
PoseGait [22]	2020	2D ConvNet	-	Identification	46.1	-
Zhang GaitNet [15]	2020	Autoencoder	LSTM	Identification	81.2	-
GaitPart [16]	2020	2D Focal ConvNet	Attention + Set Pooling + HP	-	88.8	88.7
GLN [17]	2020	2D ConvNet	Lateral Feature Pyramid + HPM	Reduction + Identification	89.4	89.2
ModelGait [24]	2020	2D ConvNet/LSTM	Temporal Average	-	89.5	95.8 ^b
MT3D [60]	2020	3D ConvNet	Set Pooling + GeM	-	90.4	-
GaitGraph [25]	2021	ResGCN	Temporal Average	Reduction	76.3	-
GaitSet [11], [12]	2021	2D ConvNet	Set Pooling + HPM	-	85.7	87.9
CSTL [20]	2021	2D ConvNet	Spatio-Temporal Attention	Identification	91.9	90.2
GaitGL [18]	2021	3D ConvNet	Set Pooling + GeM	Identification	91.8	89.7
3DLocal [19]	2021	3D Local ConvNet	Set Pooling	Reduction	91.8	90.9

^a Performance under condition of normal wearing, on CASIA-B.

^b Performance on OUMVLP, excluding invalid probe sequences.

For the models taking skeletons as input, graph convolution network [25] is adopted as an effective learner to extract structural and dynamic information.

One significant difference between gait recognition and other visual recognition is that the backbone network utilized in gait recognition is typically shallow (ranging from 4 to 8 layers). However, many visual recognition tasks exploit very deep models with tens or hundreds of layers. We analyze this phenomenon mainly because silhouettes and skeletons are two commonly used data for gait recognition, which contain relatively lower information entropy than RGB images (videos) as input. With these effective practices, such as VGG16 [120], ResNet [121], and Inception [122] *et al.*, very deep models are demonstrating the surprising performance in image classification, video understanding, and so on. This observation suggests the gait recognition to use original RGB modality instead of low-semantic silhouettes or skeletons, which take advantage of very deep models to promote precision.

4.1.2 Bottleneck networks

The bottleneck networks are typically in charge of aggregating dynamic gait information by temporal modeling and reinforcing discriminativeness of appearance characteristics by spatial manipulation.

The early practice regularly ignored the significance of designing bottleneck networks, where fully connected

layers were adopted for feature reduction and global features learning. Despite the remarkable progress in capturing holistic gait representation, such approaches still suffer from being sensitive to noise. The noise within the dataset accidentally conducts deep models fitting on failure segmentation, leading to dramatic performance degradation. Therefore, Horizontal Pyramid Pooling [12], Patch Pyramid Mapping [123], and Generalized-mean Pooling [18] proposed to capture fine-grained gait cues, which leveraged partial features to prevent overfitting. Hou *et al.* [17] introduced feature lateral learning, where the inherent feature pyramid utilizes multiple-scale features to enhance gait representations. Besides, Huang *et al.* [20] measured the importance of different parts across frames, which exploited the most discriminative parts and generated more robust Spatio-temporal representations. Considering temporal representations modeling, Set Pooling [12] proposed various feature pooling strategies along the time dimension. The Micro-motion Capture Module [16] and Adaptive Temporal Aggregation [20] made use of attention mechanism to extract gait patterns in the long-short term manner, and recurrent neural networks [114] are also able to perform adaptive temporal representation from sequential inputs.

4.1.3 Head networks

Sometimes the final head networks followed after bottleneck are optional but very useful, aiming to facilitate the

specific purposes. In object detection, there are generally two heads within deep models. Specifically, a prediction head for object recognition and a regression head for bounding box localization. Since gait recognition only considers identifying subjects but detection or segmentation, the heads within deep gait recognition are only specific for recognition.

The verification head [9] and identification head [17] are the two most classical and frequently used in the deep gait models. Although such an identification head with a strong backbone and bottleneck achieves satisfying precision, Hou *et al.* [17] argued that the dimensionality of features of previous methods is not compact enough to apply in reality. Compact block [17], [19] was introduced to reduce the representation dimension and the memory. Beyond discriminative and compact representations, there are a series of heads ranged from quality-aware [124], view-aware [125], condition-aware [126], and gender-aware [127], introducing many good practices toward multi-task gait recognition.

4.2 Single-stream Architecture

This part will summarize and introduce the single-stream architectures in gait recognition. There are three kinds of commonly used architectures from the literature: (1) template-based architecture, (2) asynchronous fusion architecture in the spatial-temporal domain, and (3) simultaneous fusion architecture in the spatial-temporal domain.

4.2.1 Template-based Architecture

Deep learning was first applied to image classification and was very successful in face recognition years ago. The single-stream architecture is the central architecture at the beginning of deep gait recognition. It is straightforward to take template images, such as GEI, as the input for gait recognition. The very beginning attempt [9] took GEI as input of neural networks and treated gait recognition as a similar task to image classification.

The classical image classification task primarily focuses on dealing with the inter-class issue. At the same time, gait recognition is a more complex problem because it also needs to deal with the problem along intra-class such as cross-view, carrying, and clothing. However, it is worth referencing those empirical practices in image classification. Inspired by classical image classification, the very beginning attempt [9] took GEIs as input of neural networks and treated gait recognition as the image classification task. This template-based architecture treats the recognition task as a traditional image classification task without carefully modeling the gait motion information. Besides, Gaitnet [61] attaches an automated segmentation module achieving the end-to-end model, and it also integrates metric learning to find more discriminative features. The typical spatial feature extractors module can be a 2D convolution neural network, deep belief network, and deep auto-encoder [114]. Although the different types of networks build within their principle, the usage is identical to spatial feature extractor.

The template-based architecture aggregates all frames into one image to represent the original gait sequence, which is a down-sample step. Recovering ordered sequences from

the template, such as GEI, is impossible. Although gait templates contain a sort of temporal information, they throw away the majority of temporal information, hugely significant to recognizing humans at a distance. Template-based methods are outstanding for their simplicity and efficiency, but they also limit the performance because of their simple fusion strategy.

4.2.2 Asynchronous Fusion Architecture

The pipeline with temporal information aggregation after spatial feature extractor is called asynchronous fusion architecture in our survey. Different from template-based architecture recognizing gait template, asynchronous fusion architecture will learn spatial representation from gait sequence, then integrate the extracted motion feature for final recognition.

GaitSet [11] [12] is a typical method following the architecture of asynchronous fusion. The stacked convolutional layers learn the spatial feature with pooling and activation layers, and Set Pooling preserves the most significant spatial-temporal feature among gait sequences. Besides, it also comprehensively studies different pooling strategies, such as max, mean, median, or joint pooling. GaitPart [16] captures the spatial information by focal convolution layers but extracts dynamic motion from the proposed micro-motion feature builder. Zhang [89] also presents a similar architecture by learning asynchronous representation from partial silhouettes. Because of various combinations between spatial and temporal feature extractors, asynchronous fusion architecture can be implemented by autoencoder with LSTM like GaitNet [15], capsule neural network with RNN [128] as well.

4.2.3 Simultaneous Fusion Architecture

For gait analysis, it is natural to capture the spatial-temporal representation simultaneously rather than staged fusion. Simultaneous fusion architecture is designed to consider discriminative features along both spatial and temporal dimensions. In this circumstance, 3D ConvNets, as a typical component, act directly on the raw data to learn spatial-temporal representation. The extracted feature is relative to spatial and contains dynamic features. Although 3D ConvNets are popular in many fields like action recognition [129] and video understanding, three-dimensional convolution structure led to more parameters than 2D convolution network because additional kernel makes it harder to train.

The first attempt by applying the structure of 3D ConvNets on gait recognition [7] has shown the high potential of the 3D convolution network, and it performs well on multiple variants such as view, clothing, and walking speed. Although the methods utilizing 3D ConvNet can provide promising results, the computation cost is still criticized by other methods based on 2D ConvNet. It leads the majority of research to pay more attention to 2D convolution. However, Lin *et al.* presented GaitGL [18] and MT3D [60] with 3DCNN as backbones, which achieved the current state-of-the-art approach and attracted increasing attention to the study using 3D convolutions. Furthermore, gaitgraph [25] utilized a spatial-temporal graph neural network to capture discriminative representation from skeleton sequence and

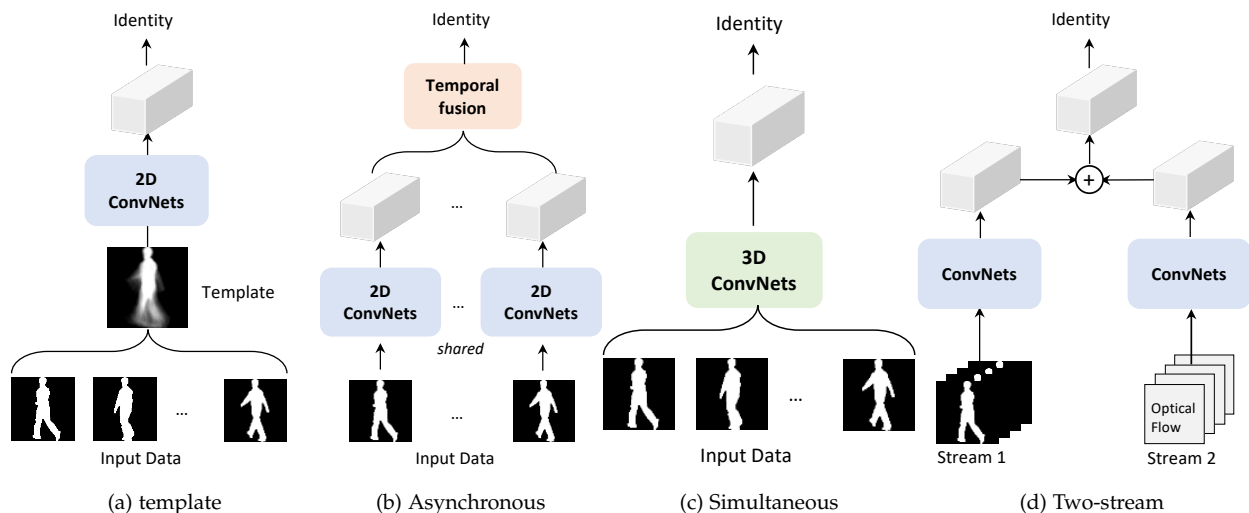


Fig. 8: Illustration of four typical architecture of deep gait recognition.

achieved state-of-the-art performance in skeleton-based gait recognition.

4.3 Multi-Stream Architecture

Since the novel two-stream architecture [130] applies in action recognition, many methods pay increasing attention to capturing information from multiple streams. The multi-stream architecture can extract more discriminative representation from various information streams and capture entire features from multiple branch streams even with the same information input [131].

The first type of architecture typically utilizes information among multiple semantic streams such as RGB images, silhouettes, optical flow images *et al.*. This concept was firstly presented by [130], and it is based on the hypothesis that the human visual cortex contains two pathways: the ventral stream to focus on object recognition and the dorsal stream to capture motion. Wu *et al.* [9] proposed a kind of two-stream convolutional network for gait recognition by combining features extracted from two commonly used templates: gait energy images and chrono-gait images. To further investigate the potential of multiple-stream architecture and a robust gait system, Castro *et al.* [132] presented multi-modality fusion architecture from three different modalities (gray, optical flow, and depth images). The multimodal fusion derived gait feature directly from raw sequential images rather than the gait template used by traditional methods. It helped outperform template-based two-stream methods with plentiful information from the raw pixel.

The alternative structure of the multiple stream network for gait recognition is typically based on the singular modality but multiple parallel networks for representation learning. One normally adopted network structure has two branches: a local branch focusing on fine-grained partial gait features and a global branch capturing holistic gait representation. This architecture is widely used in GaitGL [18], GLN [17], TS-GAN [133] *et al.*. While MT3D [60] presented two-stream along long-term and short-term to obtain the multiple-scale temporal pattern. GaitSet [12] and GLN [17]

captured set-level and silhouette-level representations from two branches architecture. The common singular stream architecture is capable of learning representation. In comparison, the two-stream structure can take both advantages from the feature fusion of multiple sources to build the final representation with robustness. Therefore, multi-stream architecture has more potential to be further investigated in gait recognition from our perspective.

5 DATASETS AND EVALUATION

Datasets are essential for gait recognition since algorithms need to be evaluated by datasets. Especially in these years, the increasing data size and deep learning greatly advance performance. In this section, all public gait datasets we can find in the literature will be introduced. In the early age of gait recognition, most datasets are about tens of subjects. Some are of hundreds of subjects. USF [27], SOTON [42] and CASIA-B [1] are three most commonly used ones. Some recent datasets normally have more subjects and more variations. The most commonly used large dataset is OUMVLP [6].

5.1 Datasets for Gait Recognition

All public gait datasets we can find are listed in Table 2. Large-scale gait datasets are essential for gait recognition. Collecting a large-scale gait dataset requires much more time, storage, and cost than a similar-sized face or fingerprint dataset. One possible solution is that the research community can work together to collect data and train methods using federated learning or other privacy-protecting learning methods. Besides, creating synthetic gait datasets using virtual human body models is also an exciting direction.

With the concerns on privacy and the privacy and data security laws, collecting a large gait dataset is much more challenging nowadays. Some laws, such as General Data Protection Regulation (GDPR) [134] from Europe and the Data Security Law of China [135], put substantial restrictions to protect our privacy and improve data security in data collection and usage. It is a challenge and a new

opportunity for the academic community to develop better methods to protect our privacy and improve the security of our society.

5.2 Evaluation Criteria and Performance Comparisons

We try to compare different gait recognition methods in this part. It is not easy since the different methods may use different datasets and evaluation criteria. The experimental protocols for the training and test sets may also differ even if they use the same dataset. However, we still selected some methods and compared them with two popular datasets, CASIA-B [1] and OUMVLP [6]. Some valuable conclusions can be drawn from the comparisons and analysis.

5.2.1 Evaluation criteria

As described in Section 2.5, the most commonly used evaluation mode in gait recognition is the identification and is not verification. In identification, the cumulative match characteristic(CMC) is widely used to evaluate methods. The first point on a CMC curve is the recognition rate of rank 1, and the second is the recognition rate of rank 2, and so on. For simplicity, some papers only report the rank 1 recognition rates. In the following part, we also choose the rank 1 recognition rate as the evaluation criterion.

5.2.2 Performance comparison and analysis

We selected some representative deep learning methods proposed in recent years and list their results in Table 1. There are more methods in the literature than those in this table. We only selected the methods with state-of-the-art performance, and their authors reported results on CASIA-B or OUMVLP. The results of different methods are sorted by year to let the readers better understand gait recognition improvement in the past years. From the results, we can find some valuable conclusions by comparing them.

Input data: Some early deep methods for gait recognition, such as Wu’s LB network [9] and GEINet [8] take GEI as the input. Then some new methods such as GaitSet [11], [12], GaitPart [16], MT3D [60], GaitGL [18] and many others take silhouette sequences as input, and achieve better results than those using GEI. It is easy to understand because a silhouette sequence contains more temporal information than the GEI generated from it. Some recent methods, such as Zhang’s GaitNet [15] step further and take RGB image sequences as their input. ModelGait [24] takes RGB images as input and extracts gait features from a human body mesh recovery model. From the trend, we can believe that gait recognition will continuously improve with more discriminative features extracted from the silhouette sequences or RGB sequences.

Some features from human body models, such as skeletons, can also be used for gait recognition. PoseGait [22] is based on skeletons extracted from RGB images using OpenPose [74]. A subsequent method GaitGraph [25] outperforms PoseGait. Their results are not as high as the ones of silhouette-based methods. There are not as many works on gait recognition with human models as silhouette-based methods. However, it is an interesting direction for further study.

Feature learning and model architecture: Some early methods, such as LB network [9] and GEINet [8] contains a single branch CNN backbone for feature extraction. Those methods were inspired directly by image classification. Later, to extract discriminative features, some sophisticated architectures were designed. GaitSet [11] has one branch for each silhouette (not GEI) and then aggregates the extracted frames-level features with set-level features from another branch. To extract temporal features, ACLGait [89] employs LSTM and shows its superiority compared with methods without temporal information. Similarly, PoseGait [22] and GaitGraph [25] use LSTM and Graph Convolutional Network (GCN) respectively. Besides, GAN [167], 3D convolution [19], [60] and disentangled representation learning [168] are also employed for feature extraction. From the previous research, we can find that spatial feature plays an important role in gait recognition. Discriminative temporal features are difficult to be extracted. CSTL [20] tries to learn context-sensitive temporal features by a network with two branches, one branch is for temporal aggregation, and another is for salient spatial features. 3DLocal [19] also pays attention to temporal feature extraction using 3D local CNN.

Metric learning: Gait recognition normally has more classes/subjects and fewer samples for each class/subject. Some loss functions have been developed after some tries of cross-entropy [9]. For example, ACLGait [89] employs Angle Center Loss and achieves promising performance. Zhang’s GaitNet [168] uses Incremental Identity Loss and outperforms other combinations of disentanglement and classification loss. Later, Siamese Network [169] and Triplet Network [170] are introduced in [171] and in the methods MT3D [60] and GaitPart [16]. Gait recognition has its own characteristics, such as high dimensional data, large intra-class variance, few samples for each class *et al.* . A suitable metric learning method is needed for gait recognition.

6 SECURITY AND PRIVACY OF GAIT RECOGNITION

In Jain *et al.* ’s overview on biometrics [172], the security and privacy have been well described. However, the description is for the whole biometrics, not specifically for gait recognition. Here we summarize the security and privacy problems and then give the specific concerns on gait recognition. With the rapid development of gait recognition, the research community and the whole society should be concerned about the possible effects of gait recognition shortly.

6.1 Security

Like other biometrics systems, gait recognition should also be secure from various attacks. There are three kinds of attacks, according to the summary in [172], presentation attacks, adversarial attacks, and template attacks.

- **Presentation Attacks** is a kind of attack by presenting artificial objects to the sensors of biometrics systems. It is very common in face recognition [173] to attack a face recognition system by presenting a face image on the iPad or wearing a 3D silicon mask. Different from face presentation attacks, few works are on gait recognition. The first investigation on vision-based gait presentation attack is by Hadid *et*

TABLE 2: All public gait datasets we can find in the literature. The related information of each dataset are also listed.

Institution	Dataset	Subjects	Sequences	Views	Variations	Environment	Available	Year
ZJU,China	VersatileGait [127]	11,000	1M	33	views occlusion	Unity3D	yes	2021
THU,China	GREW [5]	26,345	128,671	882	view, distractor, carrying, dressing, occlusion, surface, illumination, speed, shoes, trajectories	wild	yes	2021
SZU,China	ReSGait [136]	172	870	1	cl, carrying, trajectories	indoor	yes	2021
	RGB-D Gait [137]	99	792	2	views	indoor	yes	2013
OU-ISIR, Japan	OUMVLP Pose [76]	10,307	268,086	14	views	indoor	yes	2020
	OU-LP Bag [2]	62,528	177,973	1	carrying	indoor	yes	2018
	OUMVLP [6]	10,307	267,386	14	views	indoor	yes	2018
	OU-LP Age [3]	63,846	63,846	30	age	indoor	yes	2017
	Bag β [138]	2,070	4,140	1	carrying	indoor	yes	2017
	ST-1 [139]	179	-	1	speed	indoor	yes	2014
	ST-2 [139]	178	-	1	speed	indoor	yes	2014
	OU-LP clv1 [140]	4,007	7,844	1	-	indoor	yes	2012
	OU-LP clv2 [141]	4,016	7,860	1	-	indoor	yes	2012
	Speed [142]	34	612	1	speed	indoor	yes	2012
	clothing [142]	68	2,746	1	clothing	indoor	yes	2012
view [142]	200	5,000	1	views	indoor	-	2012	
fluctuation [142]	185	370	1	fluctuation	indoor	yes	2012	
UMA, Spain	MuPeG [143]	-	-	-	occlusion	indoor	yes	2020
MSU, US	FVG [114]	226	2,856	3	views, speed, carrying, cl, occlusion	outdoor	yes	2019
IPVC, Portugal	GRIDDS [15], [144]	35	350	1	trajectories	indoor	yes	2019
ISR-Lisboa, Portugal	ks20	20	300	5	view	indoor	-	2017
GPJATK	GPJATK	32	166	4	view, 3D data	indoor	-	2017
SDU, China	SDUGait [145]	52	1,040	2	trajectories views	indoor	yes	2016
WUST, Polan	BHV MoCap [146]	10	246	1	trajectories	-	yes	2015
IITs, Indian	Depth Gait [104]	29	464	2	view, occlusion, speed	-	yes	2015
PPGC-UFPel, Brasil	Kinect [147]	164	820	-	curve	indoor	yes	2015
KY, Japan	KY4D-B [148]	42	84	16	curve	indoor	yes	2014
	Shadow [149]	54	324	1	views, cl, bg	indoor	yes	2014
	KY4D-A [150]	42	168	16	views	indoor	yes	2010
A.V.A UCO, Spain	AVAMVG [151]	20	1,200	6	views, trajectories	indoor	yes	2013
WVU, US	WOSG [152]	155	-	8	views, illumination	outdoor	-	2013
ITB, Indonesian	dataset [153]	212	-	1	-	indoor	-	2012
TUM, Germany	TUM-IITKGP [154]	305	3,370	1	time, carrying, shoes	Indoor	yes	2012
	TUM-GAID [4]	35	1,645	1	times, appearance, bg, occlusions,	indoor	no	2010
UAB, Spain	DGait [51]	55	605	1	trajectories	indoor	yes	2012
IIT, Italy	RGBD-ID [155]	79	316	1	trajectories, time, cl, speed	indoor	yes	2012
QUT, Australia	SAIVT-DGD [52]	35	700	1	speed, carrying, shoes	-	yes	2011
Soton, England	Multimodal [156], [157]	300	5,000	12	views	indoor	yes	2011
	Temporal [158]	25	2,280	12	views	indoor	yes	2011
	Small [29]	12	-	4	bg,cl,carrying, speed, footwear, views	indoor	yes	2002
	Large [42]	116	2,128	2	Terrain, direction, views	in/outdoor	yes	2002
TIT, Japan	Early [29]	10	40	1	-	indoors	-	1997
	TokyoTech DB [159]	30	1,902	-	speed	indoor	-	2010
CASIA, China	CASIA-D [55]	88	880	1	multi-modality	indoor	yes	2009
	CAISA-B [1]	124	13,640	11	views cl bg	indoor	yes	2005
	CASIA-C [43]	153	1,530	1	speed bg	outdoor	yes	2005
	CASIA-A [88]	20	240	1	walking direction	outdoor	yes	2001
BUAA, China	IRIP	60	4,800	8	gender view	indoor	-	2008
GT, US	GT Speed [160]	20	268	3	views time	in/outdoor	yes	2003
USE, US	USF [27], [99]	122	1,870	2	shoes, views, carrying, terrain, time, trajectories	outdoor	yes	2002
UMD, US	Dataset-1 [161]	25	100	4	views, long distance	outdoor	yes	2001
	Dataset-2 [161]	55	222	2	views, times	outdoor	yes	2001
	Dataset-3 [161]	12	-	1	views	outdoor	yes	2001
CMU, US	CMU-mobo [162]	25	600	6	speed, carrying, inclination	indoor	yes	2001
MIT, US	MITAI Gait [163]	24	194	1	times months	indoors	yes	2001
	Early [164]	5	26	1	-	indoor	-	1994
UCSD, US	UCSD [165]	6	42	1	-	outdoor	yes	1998
NTTBRL, Japan	NIT Gait [166]	7	70	1	same cl, shoes	-	-	1995

al. [92]. They investigated how clothing could be used to spoof a target. Later they studied how to improve gait recognition to attacks in their successive work [174]. It is not a well-studied topic in gait recognition, and more work on it is expected.

- **Adversarial Attacks** are by digital synthetic data. The synthetic human motion can be generated by the method in [175]. There is also a large synthetic gait dataset, VersatileGait [127]. Currently, no work on adversarial gait attacks is found in the literature. However, it is feasible to generate walking videos for gait recognition from a subject’s walking style and his/her body appearance.
- **Template attacks** is to reconstruct images or videos from templates that are extracted by a biometrics system. Studies on face [176] and other biometric features have shown its feasibility. Unlike presentation and adversarial attacks, gait template attacks have no obvious differences from other biometric features such as the face, fingerprint, or iris. All methods to attack face recognition or against template attacks on face recognition can also be used for gait recognition. Gait template attack may be more complicated than the face because gait data is typically in a higher-dimensional space than face data. But it is not impossible.

6.2 Privacy

From the results in Table 1 and in [94], it can be obviously found that the recognition rate has been improved greatly. The recognition rate on the challenging CASIA-E dataset can reach 83.9% with a 500-subject test set [94]. It must be noted that the previously mentioned results were achieved just by the public gait datasets, which suffer from limitations on data size and variations in real scenarios. The recognition rate will be much higher with more accurate data. Moreover, better algorithms will also be developed in the future.

Gait recognition systems with high accuracy may cause more privacy problems than face recognition systems which have caused significant privacy concerns worldwide. The reason is that gait can be captured farther away than face. Wearing hats, sunglasses, and masks to protect faces is natural. However, Wearing completely different clothing to hide gait is not. Besides identity, gender and health conditions are also perceptible from gait [177].

To protect data and privacy, the European Parliament passed the *General Data Protection Regulation (GDPR)* [134] in 2016, *Data Security Law of the P. R. of China* [135] went into effect in 2021. Several states in the US also passed similar laws, such as *California Consumer Privacy Act* [178] and *Biometric Information Privacy Act* of Illinois. China also passed a national standard, *Information Security Technology—Personal Information Security Specification (GB/T 35273-2020)* [179], to give very detailed instructions. Most laws and regulations on the privacy protection of biometric data have some common principles. They are that the person whose biometric data is collected has the right 1) to know how the data will be used and stored, 2) to delete the data, and 3) to opt-out from the data usage. However, most laws mainly limit the use of biometric data on private businesses and give some

exceptions on the usage of governments for public security and other similar purposes. It is the nontransparent part of most laws.

The privacy concerns on gait recognition may bring a crisis to video-sharing social networking services such as YouTube and TikTok. There are many kinds of videos, as in Figure 9 online. If the walking pedestrians in the videos can be identified by their gait features, should we get a permit from them before posting? It is impossible to get permits from all pedestrians. Google Street has blurred all human faces on the street. Should the pedestrians in the videos be blurred also, or should those videos be deleted directly from the Internet?



Fig. 9: A shared video on the social platform with many pedestrians [180].

7 CHALLENGES AND DIRECTIONS

Even though significant progress has been achieved in the past years, there are still many challenges in gait recognition. We think gait recognition can be improved from the four aspects: accuracy, datasets, trustworthiness, and privacy protection. They are described in detail in the following part of this section.

7.1 Accuracy

Since gait recognition is to identify different persons, accuracy should be its first critical assessment. Even the best accuracy in the literature can be 93.0% (Table 1), but it was achieved without apparent variations on a relatively small dataset, CASIA-B. The variations closing to reality should be considered to design a better and more robust algorithm.

7.1.1 View variation

Silhouettes, the most popular input data, will be changed drastically when the view is changed. View variation will reduce accuracy significantly when the view of the gallery sample is different from that of the probe sample in the test phase. One possible solution is to collect data from many views and train a big model. It is pretty difficult to collect many views for many subjects. So model-based methods may reduce the affection of view since some 3D human models can be view-invariant. Some previous works [22], [25] achieve encouraging results in this aspect.

7.1.2 Appearance variation

The human body shape can be changed in images when clothing is changed. The carrying conditions and shoes can also change the shape and walking style. As found in [181], many people watch video clips or text with their mobile phones when they walk. All those factors make the intra-variance in gait recognition challenging.

7.1.3 Aging

Walking styles will change with aging. Some datasets [27], [32], [44], [182], [183] contain gait data at different times of the same subject. However, the longest period is 12 months. ReSGait [181] is with a little longer period of 15 months. The study in [184] argues that gait can be used as a stable biometric for one year. However, more research on a much larger time span, such as dozens of years, is needed.

7.1.4 Temporal feature extraction

Most gait recognition methods in the past mainly focus on spatial feature extraction. Some work [12] even argue that the temporal feature is not so important. Nevertheless, we think the temporal feature is more demanding to extract than the spacial feature from noisy silhouettes. The temporal feature is still essential to gait recognition. The problem is how to extract discriminative temporal features.

7.1.5 Few-shot gait recognition

In real applications, the captured video clip for gait recognition may be concise. Some researchers studied how few frames can be for gait recognition. In [11] an accuracy of 82% can be achieved with only seven silhouettes and is close to the best performance with more than 25 silhouettes. PAGCRNet [116] achieves an incredible 80.3% accuracy with only one frame as input. Surely temporal information will be much less in very few frames than in a whole gait cycle. It is an exciting topic among temporal feature extraction mentioned in the previous paragraph.

7.1.6 Occlusion

Occlusions are pretty common in real applications. A part of the body may be occluded by other objects, such as cars and street lamp poles, when the subject is walking on the street. Therefore, human body alignment may be needed, like face alignment in face recognition. GaitPart [16] tries to extract gait features from different body parts and can partly solve the occlusion problem. Regardless, there is not enough work on this topic.

7.2 Datasets

Gait datasets are essential to gait recognition, and collecting gait data is expensive. Nevertheless, there are still many methods to advance gait recognition.

7.2.1 Datasets in real scenarios

Most current public gait datasets were collected in controlled environments and are relatively easy to identify. In real scenarios, there are many more uncontrolled factors. Mu *et al.* [181] created a dataset, ReSGait, from a real scenarios. From the benchmark results of ReSGait, we can

find that the accuracy is low. However, the problem is that ReSGait is a small gait dataset with only 172 subjects and 870 videos. Getting permits from subjects and labeling their identifications from a controlled CCTV system is challenging. They are also the reasons that ReSGait is not large. Nonetheless, it is worth doing it to evaluate gait recognition in real scenarios.

7.2.2 Learning from synthetic data

Since it is challenging to collect gait data in real scenarios and all conditions, one possible solution is to generate synthetic gait data from virtual 3D human bodies. Synthetic data is prevalent in self-driving algorithm development [185]. In gait recognition, VersatileGait [127] is the only public, synthetic dataset. Analyzing variations such as views, clothing, carrying conditions, and shoes is very convenient and low cost. However, how defining an identity may be a problem. There are many parameters to define a 3D body and its motion. If we consider two virtual humans are two different identities, what will be the threshold of their similarity?

7.2.3 Learning from unlabelled data

Collecting a large gait dataset in real scenarios is tricky and potentially causes privacy concerns. Another possible solution is to use unlabelled data. We can find many gait data from videos online and other sources. Gait data can be automatically detected and segmented from videos. However, it is difficult to label the subjects' identities in those videos. Similar to the application of self-supervised learning, such as contrastive learning in image classification [186], gait recognition should also be benefited from unlabelled data with self-supervised learning. A suitable gait recognition deep model can be trained from unlabelled data by some self-supervised learning methods. Another advantage is that the data is from real scenarios, and many natural variations will be included and considered in feature learning.

7.3 Trustworthy Gait Recognition

Gait recognition systems should be robust to attacks and be reliable. As mentioned in Section 6.1, there are three kinds of attacks to gait recognition, presentation attacks, adversarial attacks, and template attacks. Gait recognition methods should be robust when someone wears some specifically designed clothes or presents some human body-shaped objects. DeepFake-related technologies can also generate some human walking videos to fool biometrics systems. Original gait data should not be able to reconstruct from gait templates.

Biases on race, gender, age, dress, and others may also be an issue in gait recognition similar to those in face recognition [187]. The problem should also be investigated in the future.

7.4 Gait Encryption for Privacy Protection

As mentioned in Section 6.2, the increasing accuracy of gait recognition may threaten online video-sharing. To blur or mask all pedestrians in videos will make the videos very bad, and users will lose the desire to share. One possible

solution may be to encrypt gait videos with some modifications which can fail gait recognition methods but do not hurt the visual effect. Currently, there is no research on this topic even though there are many in face recognition [188].

8 CONCLUSIONS

Gait recognition is one of the exciting research topics in biometrics, which has been dramatically improved by deep learning. The recognition accuracy keeps increasing in these years. Even though the accuracy of gait recognition is still far behind face recognition and fingerprint recognition, there is excellent potential for gait recognition. We believe gait recognition will get improved in the next few years by analyzing the methods of gait recognition in the past years.

However, there are many challenges to improving the performance. One of them is the size of gait data. Gait data is more difficult to collect than faces or fingerprints. One reason is that the data from a subject will consume much storage. The cost for storage and collection is high. Another reason is the privacy concern of gait data. The research community has agreed that all related research should follow ethical guidelines and laws. It will also create more research topics on federated learning, data security, privacy protection, etc. Gait recognition will be improved, but the research should also be guided to improve our society.

ACKNOWLEDGMENTS

This work is supported in part by the National Natural Science Foundation of China under Grant 61976144; in part by the Stable Support Plan Program of Shenzhen Natural Science Fund under Grant 20200925155017002, and in part by the National Key Research and Development Program of China (Grant No. 2020AAA0140002).

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