Gait Recognition Based on Deep Learning: A Survey

CLAUDIO FILIPI GONÇALVES DOS SANTOS, Federal Institute of São Carlos - UFSCar, Brazil
and Eldorado Research Institute, Brazil

DIEGO DE SOUZA OLIVEIRA, LEANDRO A. PASSOS, RAFAEL GONÇALVES PIRES,
DANIEL FELIPE SILVA SANTOS, LUCAS PASCOTTI VALEM, THIERRY P. MOREIRA,
MARCOS CLEISON S. SANTANA, MATEUS RODER, and JOÃO PAULO PAPA,

São Paulo State University - UNESP, Brazil

DANILO COLOMBO, Cenpes, Petroleo Brasileiro S.A. - Petrobras, Brazil

In general, biometry-based control systems may not rely on individual expected behavior or cooperation to operate appropriately. Instead, such systems should be aware of malicious procedures for unauthorized access attempts. Some works available in the literature suggest addressing the problem through gait recognition approaches. Such methods aim at identifying human beings through intrinsic perceptible features, despite dressed clothes or accessories. Although the issue denotes a relatively long-time challenge, most of the techniques developed to handle the problem present several drawbacks related to feature extraction and low classification rates, among other issues. However, deep learning-based approaches recently emerged as a robust set of tools to deal with virtually any image and computer-vision-related problem, providing paramount results for gait recognition as well. Therefore, this work provides a surveyed compilation of recent works regarding biometric detection through gait recognition with a focus on deep learning approaches, emphasizing their benefits and exposing their weaknesses. Besides, it also presents categorized and characterized descriptions of the datasets, approaches, and architectures employed to tackle associated constraints.

CCS Concepts: • **Computing methodologies** → **Machine learning**; • **Security and privacy** → **Biometrics**;

Additional Key Words and Phrases: Gait recognition, biometrics, deep learning

Claudio Filipi Gonçalves dos Santos, Diego de Souza Oliveira, and Leandro A. Passos contributed equally to this research. The authors are grateful to São Paulo Research Foundation (Fapesp) grants #2013/07375-0, #2014/12236-1, #2019/07665-4, and #2020/12101-0, to the Brazilian National Council for Research and Development (CNPq) #307066/2017-7 and #427968/2018-6, Eldorado Research Institute, as well as Petroleo Brasileiro S.A. (Petrobras) grant #2017/00285-6.

Authors' addresses: C. F. G. dos Santos, Federal Institute of São Carlos - UFSCar, Rod. Washington Luiz, 235, São Carlos, São Paulo, Brazil, Eldorado Research Institute, Av. Alan Turing, 275, Campinas, São Paulo; email: cfsantos@ufscar.br; Brazil; D. de Souza Oliveira, L. A. Passos, R. G. Pires, D. F. S. Santos, L. P. Valem, T. P. Moreira, M. C. S. Santana, M. Roder, and J. P. Papa, São Paulo State University - UNESP, Av. Eng. Luís Edmundo Carrijo Coube, 14-01, Bauru, São Paulo, Brazil; emails: {diego.s.oliveira, leandro.passos}@unesp.br, {rafapires, danielffsantos1}@gmail.com, lucas.valem@unesp.br, {thierrypin, marcoscleison}@gmail.com, {mateus.roder, joao.papa}@unesp.br; D. Colombo, Cenpes, Petroleo Brasileiro S.A. - Petrobras, Rio de Janeiro, Rio de Janeiro, Brazil; email: colombo.danilo@petrobras.com.br.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2022 Association for Computing Machinery.

0360-0300/2022/01-ART34 \$15.00

<https://doi.org/10.1145/3490235>

ACM Reference format:

Claudio Filipi Gonçalves dos Santos, Diego de Souza Oliveira, Leandro A. Passos, Rafael Gonçalves Pires, Daniel Felipe Silva Santos, Lucas Pascotti Valem, Thierry P. Moreira, Marcos Cleison S. Santana, Mateus Roder, João Paulo Papa, and Danilo Colombo. 2022. Gait Recognition Based on Deep Learning: A Survey. *ACM Comput. Surv.* 55, 2, Article 34 (January 2022), 34 pages.

<https://doi.org/10.1145/3490235>

1 INTRODUCTION

Gait recognition emerged in the last decades as a branch of biometric identification that focuses on detecting individuals through personal measurements and relationships, e.g., trunk and limbs' size, as well as space-time information related to the intrinsic patterns in individuals movements [6]. Such an approach presented itself extremely useful in the contexts of surveillance systems or hazy environments monitoring, for instance, where unique elements usually employed for biometric identification such as the fingerprint and the face are hard or impossible to distinguish.

Besides, gait recognition approaches possess some advantages regarding other biometric identification models, since hacking such architectures poses a hard task [71]. The difficulty primarily lies in the concept's intrinsic characteristics, i.e., identification based on the silhouette and its movement, whose reproduction is particularly complicated. The same is not valid for other techniques, where the individual can trick the system by hiding the face, for instance. Further, gait recognition models do not require high-resolution images and specialized equipment for proper identification, such as iris and fingerprints, for instance. Furthermore, gait recognition methods are independent of individual cooperation, while other methods require the analyzed person collaborates with the identification system.

Moreover, gait information is easily collected from distance, which stands for an enormous advantage regarding other techniques, especially when the identification is not assisted by the analyzed person, e.g., criminal investigations. Besides, since it does not require sophisticated equipment for data extraction, these methods are commonly cheaper than other approaches, majorly due to the popularization of surveillance systems and the advent of cellphones equipped with accelerometers, which transformed the burden of extracting data signals into a straightforward task.

Despite the simplicity regarding the tools mentioned above, identifying people by walking and moving is far from a trivial task. Standard gait recognition methods, i.e., which comprise data pre-processing and features extracted in a handcrafted fashion for further recognition, often suffer from several constraints and challenges imposed by the complexity of the task, such as viewing angle and large intra-class variations, occlusions, shadows, and locating the body segments, among others. A new trend on machine learning, known as deep learning, emerged in the last years as a revolutionary tool to handle topics in image and sound processing, computer vision, and speech, overwhelmingly outperforming virtually any baseline established until then. The new paradigm exempts the necessity of manually extracting representative features from experts and also provides paramount results regarding gait recognition, surpassing existing challenges and opening room for further research.

Due to the increasing number of biometric and gait recognition works developed in past years, many authors provided studies summarizing each field's main achievements. Pisani et al. [75], Khan et al. [47], and Sundararajan et al. [95], for instance, exposed the main advances regarding biometrics identification in general, while Gui et al. [25] explored the novelties regarding brain biometrics methods. Regarding gait recognition, both Wan et al. [110] and Rida et al. [79] provided a comprehensive survey comprising general topics on the context in 2018. Meanwhile, Singh et al. [89] published a study on vision-based gait recognition, while Bouchrika [7] proposed a

similar work considering smart visual surveillance. Further, in 2019, Nambiar et al. [67] summarized the works regarding gait-based person re-identification, while Marsico and Mecca [62] focused on gait recognition via wearable sensors. However, none of them focus on presenting the main advances regarding deep learning-based approaches for gait recognition. Moreover, even though there are reviews in this context [2], most of the surveyed works comprise **Convolutional Neural Networks (CNNs)** [49] and **Long short-term memory (LSTM)** [32, 55], leaving behind some relevant and novel architectures, such as Autoencoders [108], **Capsule Networks (CapsNet)** [82], Deep Belief Networks [31], and **Generative Adversarial Networks (GANs)** [23]. Therefore, the main objectives of this work are three-fold:

- to systematically introduce the most recent and significant works comprising strategies for gait recognition through deep learning approaches; and
- to provide the reader with a substantial and illustrated theoretical background regarding gait recognition, exploring its roots on biometric recognition and exposing the most popular tools employed to gait feature extraction and the architectures used to tackle the associated constraints; and
- to present an illustrated, categorized, and characterized catalog of the public datasets available for the task of gait recognition.

Regarding the selection of the reviewed papers, the keywords employed in the search were “gait recognition using *deep learning technique*,” such that *deep learning technique* was replaced by the architectures themselves, e.g., convolutional neural networks, LSTM, and so on. Another filter considered was the work’s innovation, i.e., papers with similar techniques and architectures were discarded. Finally, the studies considered in this research were published five years ago at most.

The remainder of this work is presented as follows: Section 2 presents a theoretical background regarding the concepts and available methods for biometric detection, bestows an overview regarding the deep learning techniques employed in this work, and revisits the main concepts regarding gait recognition. Further, Section 3 introduces the most recent approaches using deep learning for gait recognition. Besides, the section also provides a brief discussion regarding the surveyed works. Datasets employed for the task are presented in Section 4. Finally, Section 5 presents the conclusions and future works.

2 THEORETICAL BACKGROUND

This section presents a theoretical background introducing the problem of biometric identification, describing the deep learning approaches employed for gait recognition, and a detailed introduction regarding the problem of gait recognition.

2.1 Biometric Identification

The problem of people identification poses a challenging task for humankind since long before the existence of computers, when specialists were responsible for analyzing and comparing documents, signatures, and other features in a handcrafted fashion to present some restricted information or to allow some banking transaction, for instance. The importance of an accurate identification was intensified insofar as the society informatization progressed, leading to the necessity of robust solutions for individuals’ recognition. In this context, a wide range of techniques emerged in the literature as alternatives for effectively identifying people through images or another biometric means.

To be considered a biometric qualification criterion, a candidate feature must meet the following conditions [39]:

- **Universality:** each person should have the characteristic;
- **Distinctiveness:** any two persons should be sufficiently different in terms of the characteristic;
- **Permanence:** the characteristic should be sufficiently invariant over a period of time;
- **Collectability:** the characteristic can be measured quantitatively.

However, in a practical biometric system, other issues should also be considered, including:

- **Performance:** which refers to the achievable recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as the operational and environmental factors that can affect the accuracy and the speed;
- **Acceptability:** which indicates the extent to which people are willing to accept the use of a particular biometric identifier in their daily lives;
- **Circumvention:** which denotes the easiness the system is fooled through fraudulent methods.

Among such techniques, the fingerprint, iris, face, and gait recognition stand out. The next section briefly revisits some of these biometric approaches.

2.1.1 Fingerprint Recognition. Formally known as dactyloscopy, fingerprint recognition systems are widely used due to the singularity of the ridges and furrows on the surface of a finger, which provides an intrinsic characteristic for each individual [54]. Moreover, such features are steady and poorly degraded over time, making the creation of a digital fingerprint image database extremely reliable.

The first model for fingerprint recognition was designed in the late 1960s, based on a system created in the XIX century by Francis Galton called Galton points [65]. Since then, many works addressed the problem through different perspectives, such as digital image processing [3, 137], Generative Adversarial Networks [125], and filter representation [50], to cite a few.

Fingerprint recognition systems are considered the most reliable and accurate biometric identification system. Nevertheless, the field is still facing several challenges, such as unsatisfactory accuracy under non-ideal conditions and security issues such as spoofing attacks. In this context, Hemalatha et al. [29] present a systematic review comprising the most recent techniques employed to deal with the drawbacks mentioned above and others.

2.1.2 Iris Recognition. The term iris denotes a colorful thin circular structure in the eye responsible for controlling the pupil diameter, as well as the amount of light that reaches the retina. Such a structure presents a great advantage for people's identification, since it is consistent against alterations on environmental conditions and generally suffers low degradation over time. Moreover, iris recognition is among the most accurate, low-cost, and convenient identification methods, since it is performed by image and does not require contact with the person [112].

Most commercial models employing iris recognition are developed based on the identification of iris' lower and upper limits using an integral-differential operator [46], even when using eyelid demarcation. Such an operator assumes the pupil is circular and acts as an orbicular border detector. Further researches introduced distinct mathematical operations to the process to make it more flexible and robust, such as parabolic curve identifiers and normalizations, to cite a few.

Moreover, a different approach was proposed by Garagad and Iyer [22], which considers a scale- and slope-invariant method that radially draws the iris region for feature extraction. The method segments the pupil's central area using concentric circles and discards irrelevant regions using discontinuity detection techniques. Besides, the method is straightforward if compared to the

approach mentioned above, since it does not use integral-differential operators, even though its effectiveness is confirmed by hit rates above 83%.

Recent studies toward iris recognition aim to overcome some challenges in the field, such as the adverse noise caused by specular reflections, the absence of iris, gaze deviation, motion/defocus blur, iris rotation, and occlusions due to hair/eyelid/glasses/eyelash [111]. Besides, He et al. [27] discuss how new trends towards long-distance iris recognition have been tackled recently and the future trends to deal with the problem.

2.1.3 Face Recognition. Face recognition is a prominent biometric system extensively used in identification and authentication systems in the most diverse areas, such as banks, military services, and public security [139]. Such methods became popular in the early 90's when Turk and Pentland proposed the Eigenfaces method [105]. In the following decade emerged several approaches so-called holistic, which are derived from low-dimensional distribution representations, such as linear sub-spaces [18] and sparse reproduction [17], among others.

Nevertheless, the major drawback regarding holistic methods lies in the intolerance to face positioning change, thus leading to a search for characteristics based methods. In this context, emerged the **Local Binary Patterns (LBP)** and the Gabor feature-based classification, achieving relevant results through filters embodying invariant properties. Later on, subsequent works started to focus on local descriptors-based approaches for face recognition [51]. In short, the objective of these methods is to train spatial filters for image feature extraction, such that the difference between images from the same person is minimized. However, the distance between features extracted from different people should be maximized. Even though such methods obtained consistent results, techniques considered "shallow," in general, suffer from inevitable limitations due to the non-linear complexity of the face variations.

A few years ago, a counterpoint for such approaches arose after the AlexNet neural network had won the ImageNet [48] competition. Since then, deep learning models gained attention in diverse areas of biometrics, including face recognition. A particular family of networks known as Convolutional Neural Networks was the first to achieve a level of recognition near humans, i.e., the DeepFace [97]. The model composed of six convolutional layers achieved accuracies less than 0.2% different from one human competitor (97.35% against 97.53%). Nowadays, the model is considered relatively simple when compared to popular architectures, like Inception [96].

Even though face recognition approaches evolved to unprecedented standards in past years, the field is still facing several challenges in terms of expression, pose, illumination, aging, and face partially or entirely obstructed by masks or veils. Recent research presented by Tiong et al. [102] suggests using multimodal biometrics to tackle the issue. Besides, Jaraman et al. [40] describe the most relevant alternatives freshly employed for face recognition in the last years, which comprise local and global features, neural networks, and deep learning-based approaches.

2.1.4 Multimodal Biometric Recognition. One of the main advantages of the human brain towards individual recognition over computer-based approaches concerns the ability to simultaneously evaluate multiple modalities of descriptive information, such as face, gait, and hair and eyes color. To adapt to this trend, a new paradigm of biometrics recognition emerged, the so-called "multimodal biometrics." Such an approach aims at combining distinct biometric recognition methods and auxiliary information to improve the performance and reliability when considering a single technique. In this context, Sultana et al. [93] proposed a person recognition approach based on a combination of visual cues, such as face and ear, with the person's social behavior. Experiments over semi-real datasets provided a significant advantage over standard biometric systems.

A recent work proposed by Li et al. [53] implements a finger-based multimodal biometrics system that considers a fusion strategy to extract correlated features from different modalities of

finger patterns, i.e., finger veins and knuckle print, obtaining state-of-the-art results over finger recognition methods. A similar work proposed by Tiong et al. [102] implements a multi-feature fusion convolutional neural network for multimodal facial biometrics, obtaining competing results over several benchmarking datasets.

The major advances of multimodal biometrics recognition are described in a systematic review presented by Dargan et al. [13]. The authors provide a literature review concerning unimodal and multimodal biometric systems, datasets, feature extraction techniques, classifiers, results, efficiency, and reliability. Besides, they also discuss how multimodal biometric approaches can be employed to overcome some common challenges faced by unimodal methods, such as face, finger-print, and iris recognition.

2.1.5 Other Identifiers. For different reasons, the traits mentioned so far may not be interesting in certain environments, either due to the imprecision of the model or the lack of specialized equipment for the correct identification. Among some unusual approaches, Ragan et al. [77] showed that ear-based biometrics has intrinsic characteristics capable of holding unique information from individuals. Applications can be observed in smart-phone-based applications.¹ Meanwhile, Ramli et al. [78] employed the heartbeat rate pattern for biometric identification. The method obtained significant accuracy and also has been employed for unlocking electronic devices.² Similarly, Chen et al. [8] offered a Raspberry Pi-based system for gesture recognition on an Internet of Things environment. The same group of authors [19] presented a study comparing several machine learning approaches for human activity recognition.

As described in Section 2.1.2, the characteristics of the eye present powerful descriptive biometric features, such that iris recognition plays the leading role in this context. However, some distinct approaches have been successfully employed for the task. The research developed by Ma et al. [58], for instance, showed the eyes' movement pattern while following objects is unique in each person and employed such a feature for portable remote authentication smart grids. A study proposed by Zehngut et al. [131] has shown that it is possible to divide the types of noses between six different groups and, combined with specific proportions of the width and height of the nose, enable the identification of individuals with accuracy as good as recognition by iris. Among the method's advantages, one can highlight its visibility in almost 100% of cases, even when people use glasses or hats. The major disadvantage regards plastic surgery, changing features relevant to the correct identification of the individual.

The main drawback regarding image-based biometric systems, e.g., fingerprints or irises methods, lies in the susceptibility to malicious attempts to fool the system. In short, a simple image could fool such systems, granting access to someone else's information in a bank account, for instance. However, some more sophisticated methods can identify people by fancier characteristics, such as the veins configuration [1]. The method is more robust against fraud than simple image-based techniques, since it demands specialized equipment for proper identification.

2.2 Deep Learning Approaches Considered for Gait Recognition

Even though standard machine learning and gait recognition strategies provided relatively satisfactory results in past years, such methods are usually constrained to hand-crafted features and limited capacity for learning intrinsic patterns in data. In this context, deep learning-based approaches emerged as an elegant solution for tackling image/video and sequential problems, among others, also revealing themselves as a powerful tool for gait recognition. Thus, this section presents

¹<https://www.popsoci.com/article/technology-tested-app-authenticates-you-shape-your-ear>.

²<https://www.extremetech.com/computing/165537-nyimi-wristband-turns-your-heartbeat-into-an-electronic-key-that-unlocks-your-devices>.

Fig. 1. An example of 3×3 convolution.

Fig. 2. A standard CNN architecture's example.

the most popular deep learning architectures once employed for gait recognition, namely, Convolutional Neural Networks [49], Recurrent Neural Networks [43], Autoencoders [5], Capsule Networks [82], Generative Adversarial Networks [23], and Deep Belief Networks [31].

2.2.1 Convolutional Neural Networks. Convolutional Neural Networks [49] obtained exceptional popularity since the beginning of the 2010s, becoming paramount to solve image processing-related problems, such as image classification [101] and segmentation [138]. As the name suggests, CNNs basic blocks are composed of convolutional neurons, usually composed of 3×3 or 5×5 kernels, which are responsible for performing convolutional operations over the input data. Briefly speaking, this process's output generates a new set of matrices, which are then employed as the subsequent layers of the model. In signal processing, convolution is described as a multiplication of two signals to generate a third one [72]. Figure 1 depicts the idea.

Therefore, a CNN can be interpreted as a stack of convolutional kernels generating the successive layers' input. Notice some intermediate pooling layers may be included in the process, and a fully connected layer is coupled at the top of the architecture for classification purposes. The learning process is performed by the backpropagation algorithm working with a gradient descent calculation. Figure 2, inspired in LeNet-5, pictures a CNN architecture.

2.2.2 Capsule Networks. Even though CNNs work very well for image features' understanding, they are prone to confuse spatial relationships between complex peculiarities. In other words, a trained CNN is usually capable of recognizing dogs if it finds a dog's body, face, tail, and so on, even if the dog is assembled in a different sequence or if its parts are located in distinct sections of the image. However, Capsule Networks [82] consider a hierarchical approach to tackle this problem. In short, the model comprises a two-layer structure. The first is a convolutional encoder, which performs the recognition of low-level features. The second stands for a fully connected linear decoder

that employs the routing by agreement algorithm [82] to address such low-level features to the correct position in a hierarchical higher-level. Therefore, CapsNets are more robust to object orientation. Besides, they may perform better for identifying multiple or overlapping objects in a scene.

2.2.3 Recurrent Neural Networks. Many works addressed the gait recognition problem as a sequence of images defining the individual's movement. A standard method to acknowledge such strategy using deep learning concerns RNNs [43], which compute each neuron's activation considering the information from the input data, as well as other neuron's output, in a recurrent fashion. Occasionally, the architecture is combined with a CNN to extract more information about the input images to perform the inference.

Since describing a person's gait usually requires a considerable amount of sequential features, a particular set of RNNs, namely, gated RNN, are more suitable for the task due to their abilities to deal with long sequences. In this context, one can refer to two main architectures, i.e., the Long-Short Term Memory [32] and the **Gated Recurrent Unit (GRU)** [10].

- (1) **Long-short Term Memory:** The Long-short Term Memory was first implemented in 1997 by Hochreiter and Schmidhuber [32], where the main objective was to improve results on long sequences of data. In a nutshell, LSTMs work similarly to the traditional RNN, i.e., the output of a given neuron depends on recurrent information from previous neurons' outcomes. The main difference lies in the LSTM cell's architecture, which comprises more complex and fancy relationships. Such an architecture is composed of three main gates that control the flow of information, described as follows:
 - The forget gate: This gate defines how much of the information should be kept. The previous and current state data is passed through a sigmoid function, which outputs values between 0 and 1. The closer to 1, the more information is preserved.
 - The input gate computes a new value to update the current hidden state. The input gate considers two central values: (i) a sigmoid function calculates the importance of the previously hidden state, and (ii) the original value is forwarded to a hyperbolic tangent (tanh) function, which is responsible for squishing this value between -1 and 1 . The multiplication of these two values defines the current hidden state.
 - The output gate: After estimating the forget and the input gates, the output gate defines the cell's output value. The process is performed as follows: (i) the values from the forget and the input gate are summed up and submitted to a tanh function, (ii) the cell's previous state is submitted to a sigmoid function, (iii) the output from both the sigmoid and the tanh functions are multiplied, yielding the cell's output.
- (2) **Gated Recurrent Unity:** The Gated Recurrent Unit [9] is a recurrent neural network originally idealized to improve results on neural machine translations. Like LSTMs, GRUs possess internal gates that control the flow of information, and the main difference lies in the number of gates available in each model, i.e., GRU comprises only two, namely, the forget and the output gates, instead of three. Studies show that, even though the GRU uses fewer gates than LSTM, it can reach similar results [10], with the advantage of a reduced computational burden and faster performance considering both tasks of training and inference.

2.2.4 Autoencoders. Autoencoders [108] are generative neural networks usually employed for data reduction and image denoising. The model comprises two main steps, described as follows:

- Encoder: It is responsible for encoding the input information into a, usually, smaller feature space.
- Decoder: It performs the unsupervised reconstruction of encoded data.

Figure 3 depicts the architecture of the model.

Fig. 3. A standard autoencoder architecture.

Fig. 4. A standard GAN architecture.

2.2.5 Deep Belief Networks. Deep Belief Networks [31] are stochastic neural networks ideally designed for generative tasks, such that each layer denotes a greedy-fashioned trained **Restricted Boltzmann Machine (RBM)** [31]. In short, RBM is a graphical model composed of a visible and a latent set of units, namely, visible and hidden layers, respectively, which are connected by a weight matrix with no connection among neurons from the same layer. The model's learning approach consists of attaching a collection of input data into the visible layer and finding a representation of this data in the hidden units. Besides, the training procedure is performed by minimizing the system's energy, usually conducted using a Markov chain procedure through Gibbs sampling for optimization purposes.

Concerning classification tasks, the most common approach considers coupling a softmax layer at the top of the DBN architecture and, after greedily pre-training all the RBMs, performing a fine-tuning in the weights using Backpropagation, for instance, to adjust the weight matrices and fitting the labels for proper identification.

2.2.6 Generative Adversarial Networks. Generative Adversarial Networks [23] became popular in the past years due to their outstanding ability to generate realistic synthetic images. The model comprises two distinct networks, i.e., a generator, which is responsible for learning the data's distribution and generating synthetic samples, and a discriminator, which tries to identify whether a given instance is original or synthetically created. The generator and the discriminator compete in an adversarial fashion such that the generator attempts to generate samples realistic enough to fool the discriminator. In contrast, the discriminator improves itself more and more to recognize such fake images. Figure 4 illustrates the model.

2.2.7 Deep Learning Techniques' Summary. Table 1 presents a summary concerning the deep learning techniques considered in this work and how they are usually employed for gait recognition tasks. Notice that the same work can eventually use distinct architectures, thus appearing more than once in the table.

Table 1. Deep Learning-based Gait Recognition Approaches Organized by Type of Neural Network

References	Technique	Task
[52, 86, 90, 91, 98, 115, 116, 119, 126, 139]	Convolutional Neural Networks (CNN)	Feature extraction from images or frames of a video.
[5, 132]	Auto Encoder	Works by compressing and decompressing features from the input.
[85, 121, 133]	Capsule	Improve the semantic organization of the outputs from a CNN.
[21, 118]	Deep Belief Networks	Encode features and patterns into compressed representations.
[28, 35, 41]	Generative Adversarial Networks	A training method that relies on the differentiation of an original input and a generate counterpart from a model, such as a CNN.
[76, 103, 115, 132, 139]	Recurrent Neural Networks	Comprise both GRUs and LSTMs, which are composed with several gates to control the flow of information and are employed to deal with temporal information.

2.3 Gait Recognition

Several methods for people recognition through biological characteristics have been presented so far. Although the methods' reliability and safety are confirmed by their success in banks and public governance systems, two main hindrances must be stressed: (i) they depend on the passive provision of personal biometric information, i.e., the person must provide or register the required information for the recognition; and (ii) some of these systems rely on specialized equipment.

An alternative to deal with such drawbacks may comprise gait recognition models, especially considering video-based approaches. Such methods do not suffer from the problems mentioned above, once the acquisition of the biometric information depends, most of the time, only on a camera with no specific features or non-evasive sensors and devices, and, disregarding legal problems, the collection of such information is performed passively. Therefore, the observed person is no longer required to cooperate in the identification process or provide any information. However, although video-based recognition is the most intuitive method, it does not stand for the only possibility. Gait identification can also be performed by distinct characteristics, e.g., the footprint [11], which considers the pressure and size of the area. The obvious disadvantage of such models is the cost of deploying the equipment necessary to acquire such features.

Moreover, techniques proposed for gait recognition can be divided into two main groups, i.e., template- and non-template-based methods. Template-based methods aim to obtain the movement of the trunk or legs, i.e., they usually focus on the dynamics of movement through space or spatio-temporal based methods [123]. Among such techniques, one can refer to **Walking Path Image (WPI)** information [134], **Gait Information Image (GII)** [4], and **Gait Energy Image (GEI)** features, which can be extracted through Canonical Correlation Analysis [56], Joint Sparsity Models [124], segmentation using Group Lasso Motion [80], among others [52, 86, 116]. However, non-template based methods consider the shape and its attributes as the more relevant characteristics, i.e., the recognition of the individual is performed with measurements that reflect its shape [16].

Fig. 5. Example of gait data acquisition environment. The scene comprises the following devices: sidewall cameras, followed by a multi-spectrum photographic sensor. The roof accommodates velocity sensors and gyroscopes, which measure the space-time relationship during the walk. Finally, the floor is equipped with a carpet-like sensor for collecting the foot pressure on the ground, completing the gait cycle.

Regarding the process of gait information acquisition, it may comprise several sorts of sensors and devices, as illustrated in Figure 5. The image depicts a laboratory-like environment designed with several embedded devices for gait data acquisition, such as cameras, which are the most commonly employed device for the task, since they are quite accessible and are capable of acquiring data over greater distances, and multispectral photographic sensors that are very efficient, but with less accessibility due to high costs. The image also comprises gyroscope and velocity sensors on the roof, responsible for describing the spatio-temporal context acquisition. Finally, the walking rhythm is measured using a step-pressure carpet-like sensor, which is highly valuable to detect gait abnormalities, such as the ones caused by Parkinson's disease and other neurodegenerative problems.

Despite the success obtained by the methods mentioned above, deep learning-based approaches induced a paradigm shift in the field of gait recognition, obtaining paramount results in a variety of applications. Therefore, the next section introduces an in-depth presentation of several surveyed works in the context of deep learning-based approaches for gait recognition. Figure 6 provides a schematic diagram comprising an overview of the main differences between deep learning and the standard methods for gait recognition.

3 GAIT RECOGNITION THROUGH DEEP LEARNING-BASED APPROACHES

This section presents a systematic review of recent works using distinct deep learning architectures, i.e., Convolutional Neural Networks, Recurrent Neural Networks, Generative Adversarial Networks, Deep Belief Networks, and Autoencoder-based approaches for gait recognition. Besides, it also presents a discussion regarding the compared methods and a summary of the surveyed studies.

3.1 Convolutional Neural Networks

Convolutional Neural Networks [49] use a concept of a neuron based on the visual cortex of mammals, which was first validated for the task of digit classification and today is probably

Fig. 6. Schematic diagrams from deep learning (top) and standard (bottom) gait recognition pipelines. As the image suggests, deep learning approaches abstract the steps concerning data pre-processing, feature extraction, and classification in a single architecture.

the most widely employed neural network for classification, reconstruction, and object detection, among others. In the context of gait recognition, Shiraga et al. [86] used an architecture similar to LENet [49] to create a gleaming-based recognizer through **Gait Energy Image (GEI)**. The model achieved an accuracy of 91.5% in the OU-ISIR [59] Large Population dataset. A similar work proposed by Wang et al. [113] employs nonstandard periodic GEI approaches for gait recognition and data augmentation.

Regarding cross-view gait-based human identification, Wu et al. [116] claim to propose the first work using CNNs in the context of grimace recognition. The authors employed several network architectures and demonstrated the power of CNNs in the context of biometric-based identification, obtaining gains above 10% to previous results. Besides, they also compared three types of data arrangement, described as follows:

- *Local Bottom*: A combination is made among the input data, and then it is determined whether the inputs belong to the same or different individuals;
- *Mid-level Top*: The neural network extracts some characteristics of both inputs before combining them and then determining whether or not they come from the same person; and
- *Global Top*: Similar to the previous network. However, it has an extra level of convolutions and *Perceptrons*, such that the combination of characteristics is made in the penultimate layer.

Further, Li et al. [52] proposed the DeepGait, a model that combines deep convolutional features and Joint Bayesian for video sensor-based gait representation. The model outperformed hand-crafted features, such as GEI, Frequency-Domain Feature, and Gait Flow Image, obtaining state-of-the-art results over OU-ISR large population dataset [59]. Meanwhile, a study proposed by Sokolova and Konushin [90] demonstrated the difficulty in identifying people by their behavior due to the intersection of information, despite satisfactory results over TUM-GAID database [33], obtaining 97.5% accuracy and 99.89% Rank-5. However, the performance was severely degraded concerning CASIA B dataset [127], bringing an accuracy of 58.20% over such a scenario, demonstrating how this type of biometry is sensitive to the data's context.

The same authors proposed a multiple-stage model for gait recognition using **Optical Flow (OF)** [91]. In this model, the data is pre-processed in two main steps: motion map computation

and frame-by-frame evaluation of the individual's pose. Further, two distinct neural networks, i.e., VGG-19 [88] and **Wide Residual Network (WRN)** [130], are employed to validate the technique in the context of video-based gait recognition. To increase classification speed, they incorporated the **Principal Component Analysis (PCA)** for dimensionality reduction. Such information goes through the normalization $L2$, and finally, the features produced are fed to a **Nearest Neighbor (NN)** classifier. Using this combination of methods, they achieved very accurate results over TUM-GAID [33], CASIA B [127], and OU-ISIR [59] datasets.

Recently, an architecture called Siamese Networks, which accepts two separate entries as input and computes a similarity value between them, was successfully employed for similar tasks, such as identifying obstructed routes or misbehavior in hazardous environments [83]. In this context, Takemura et al. [98] implemented four different frameworks to create a biometric identification system. All networks rely on GEI to make the comparisons. Two of these networks were developed based on the Triplet Ranking Loss, which necessarily needs three inputs for execution: (i) the information of the compared person, (ii) data from the same person, and (iii) an entrance from any other person. The other two networks use contrastive loss in their execution, whose entries depend only on the person's information for comparison. The authors obtained 91.9% of accuracy over the **OU-ISIR Multi-view Large Population (OU-MVLP)** [99] database.

Still, Xu et al. [119] proposed the Pairwise Spatial Transformer Network, a unified model composed of pairwise spatial transformers and a recognition network for cross-view gait recognition. The model computes non-rigid deformation fields to match input pairs into intermediate frames, which are compared against a deformation suffered from source view to target. Experiments conducted over the OU-MVLP [99], **OU-ISIR Large Population (OU-LP)** [36], and CASIA B [127] datasets grant the model robustness.

3.2 Capsule Networks

Another well-known type of deep architecture employed for gait recognition is the Capsule Neural Network [82]. The network has been developed for image classification by modeling the hierarchical relationships between objects, i.e., capsules, in a scene. In this context, Xu et al. [121] explored such features to propose two architectures for gait recognition:

- using the **Local Bottom Feature (LBC)** combination of local features, which employs two input images and computes the differences between them in a unique network flow; and
- employing the so-called **Matching Mid-Level Feature (MMF)** to combine both images' characteristics after passing through a specific part of the neural network.

In summary, the first architecture merges the images before inputting them to the neural network, while the other combines the images after going through two layers of transformations. Experiments considering GEIs, **Chrono-gait image (CGI)**, and resolution of the input image present an identification accuracy of 74.4% over OU-ISIR [59] dataset.

In a similar work, Sepas et al. [85] used capsule networks to develop a model capable of learning more discriminative features by transferring multi-scale partial gait representations. The model employs **Bi-directional Gated Recurrent Units (BGRU)** to learn the co-occurrences and correlations among patterns and further uses a capsule network to extract deeper relationships among such features. Experiments conducted over CASIA B [127] and OU-MVLP [99] assesses the superiority of the model against state-of-the-art approaches, especially when considering challenging conditions.

Finally, Zhao et al. [133] introduced an automated learning system called **Associated Spatio-Temporal Capsule Network (ASTCapsNet)**. The model was trained over multi-sensor datasets to show that multi-modality data is more conducive to gait recognition. The model's effectiveness

is confirmed on the experiments conducted over several datasets, in which results are compared to state-of-the-art approaches.

3.3 Recurrent Neural Networks

Concerning Recurrent Neural Networks [43], Wang and Yan [115] used the Long short-term memory [32], a popular RNN architecture capable of learning long-term dependencies for cross-view human gait recognition based on frame-by-frame GEIs. Experiments conducted over CASIA B [127] and OU-ISIR [59] Large Population datasets demonstrate the model's robustness over several baselines.

A similar work proposed by Potluri et al. [76] employed LSTMs to detect gait abnormalities through a wearable sensor system. The experiments were conducted over a set of data extracted from 10 healthy individuals, such that 7 behave normally, while the three remaining simulate specific gait abnormalities, i.e., sensory ataxic, Parkinson's gait, and hemiplegic gait. The experiments focus on employing advanced technologies for gait-based diagnosis and treatment assistant systems. Other models combined specific information, such as data obtained from accelerometer and gyroscope, for gait recognition through deep learning-based approaches, reaching recognition rates above 91% [140].

Recently, Tran et al. [103] proposed an **Inertial Measurement Units (IMUs)**-based gait recognition approach. The authors employed LSTMs to exploit the temporal information on video sequences, thus extracting hidden patterns inside such sequences. Experiments conducted over whuGAIT [140] and OU-ISIR [59] provided state-of-the-art performance for both verification and identification tasks.

3.4 Autoencoders

Babaei et al. [5] also proposed a multiple-stage model for the recognition of gestures. The work tackles a problem commonly observed in several GEI-based identification datasets, i.e., the person's cycle of movement is not entirely formed. In other words, the data available for identification is not complete. To deal with the problem, the authors proposed an autoencoder-based approach called **Incomplete to Complete GEI Network (ITCNet)**. The model was trained to reconstruct the missing images using examples from the training set with a complete cycle. The network consists of nine fully convolutional networks, each responsible for 1/9 of the components of the cycle. Further, PCA is employed to compute the main features and an RNN is used for gait recognition. The model presented an index of 86% and 95% for Rank-1 and Rank-5, respectively, over OU-ISIR Large Population dataset [59] using only 20 images per instance.

Autoencoders can also be employed to extract distinct GEI features. In this context, Yu et al. [126] proposed a study using **Stacked Progressive Auto-Encoders (SPA-E)** [45] with appropriate changes for the extraction of invariant characteristics of an individual's behavior. In short, the model extracts information from independent components of the scene, such as clothes and other objects the person may eventually be carrying, instead of the movement exclusively. Experiments conducted over CASIA B [127] and SZU RGB [128] datasets show that, despite the GEI information for personal identification, intermediate and last layers also provide relevant characteristics regarding such components. Finally, the work combines such information and performs a dimensionality reduction step through PCA.

Zhang et al. [132] also employed autoencoders for gait recognition. The authors used the technique to tackle a common issue faced by biometrical recognition literature, i.e., dealing with clothes blocking body members' views, such as arms and legs. The main problem concerning such occlusions is the difficulty of reading the movements and recognizing other features such as ligaments and the point of contact with the ground. To minimize the problem, they used autoencoders to

disconnect the images' pose and appearance characteristics for further linking those characteristics to another architecture of recurrent networks to analyze the way the person gaits. Besides, the authors also propose the **Frontal-View Gait (FVG)** dataset. The system proved to be particularly robust when filming the person walking towards the camera, whose angulation is more complicated due to the difficulty of obtaining specific characteristics, such as the distance walked by each step.

3.5 Deep Belief Networks

Deep Belief Networks (DBNs) [31] are stochastic neural networks constructed using Restricted Boltzmann Machines [30] as building blocks. Such models became very popular due to their ability of performing several tasks, such as feature selection [15], classification [81], and image reconstruction [73, 74], among others. Regarding gait recognition, Fernandes et al. [21] employed DBNs to support gait assessment in the diagnosis of Parkinson's and movement disorder diseases. The authors employed wearable sensors to extract features from the subjects and performed a comparative classification analysis of Parkinsonian gait, confirming that DBN-based approaches are suitable for the task.

Further, Xiong et al. [118] demonstrated how to encode patterns using **surface electromyography (sEMG)** through Deep Belief Networks. The authors consider the knee and ankle joint angle during walking to estimate a combination of four-time domain features. The work showed a high potential for gait tracking problems.

3.6 Generative Adversarial Networks

A very interesting work by Hu et al. [35] introduces Generative Adversarial Networks [23, 92] to the context of gait recognition. The authors propose the **Discriminant Gait Generative Adversarial Network (DiGGAN)** to extract view-invariant gait characteristics for cross-view gait recognition. Experiments conducted over OU-MVLP [99] and CASIA B [127] outperformed state-of-the-art results, demonstrating the model's capabilities.

Meanwhile, He et al. [28] proposed the **Multi-task Generative Adversarial Networks (MGANs)**, a GAN-based network designed to learn view-specific gait features through the so-called **Period Energy Image (PEI)**, a multi-channel gait template proposed to tackle the problems of view angles' variation faced by cross-view methods and loss of temporal information faced by GEI-based approaches. The model employs a view-angle manifold to extract more significant features from video sequences, thus providing competitive results over OU-ISIR [59], CASIA B [127], and USF against various works available in the literature.

Further, Jia et al. [41] studied methods to avoid attacks in gait recognition systems through GAN-generated syntactic image sequences. In such a scenario, the authors proposed a GAN-based approach capable of rendering fake videos from source walking sequence with realistic details. The method is compared against two state-of-the-art gait recognition systems, and results are analyzed under attacking scenarios considering both CASIA A [114] and CASIA B [127] datasets. The effectiveness of the model is verified in both attacking detection ability and visual fidelity.

3.7 Discussion

Table 2 provides a summary of the surveyed studies presented in this section. In general, Convolutional Neural Networks are the most popular choice when considering deep learning solutions, especially concerning image/video-based issues, including gait recognition. Such behavior is expected, since CNNs obtained outstanding results in various applications and won most of the benchmark challenges in past years. Nevertheless, the other architectures also provide a valuable contribution to the field, performing better for several specific tasks.

Capsule Networks, for instance, are capable of extracting partial gait representations in a hierarchical fashion, providing better results for cases where individuals or objects are presented in the scene with multiple orientations or overlapped. Similarly, Recurrent Neural Networks are paramount to deal with sequential data, such as videos, thus presenting themselves as an essential tool for this kind of gait recognition approach.

Although most deep learning-based approaches for gait recognition comprise image/video domain, other data sources, such as accelerometers, gyroscope, sensor-based, and handcrafted features in general, also provided impressive results in a considerable number of works. Most of these works address unsupervised deep learning approaches in the process, such as autoencoders and DBNs, which usually are more expressive over these data types, while CNNs are paramount when dealing with raw image/video files. These unsupervised methods can extract information regarding the data distribution and manipulate it, usually in a lower-dimensional space, providing more representative features for gait recognition.

Finally, Generative Adversarial Networks describe a particular case when gait systems can learn a broader range of features, such as orientations, clothes, number of individuals in the scene, and so on, since they can generate synthetic data for training models. Besides, they are also useful for evaluating frauds in gait-based systems for security purposes by producing fake images for testing purposes.

Concerning the most-used methods to represent gait image data, Gait Energy Image reflects the sequence of a simple energy image cycle using the weighted average method. Further, the sequences in a travel cycle are processed to align the binary silhouette [42]. Therefore, GEI maintains the static and dynamic characteristics of human walking and significantly reduces image processing's computational cost. From an in-depth analysis of the method, one can observe a few points that characterize the model [26], described as follows:

- GEIs are a little sensitive to silhouette noise in individual pictures.
- It focuses on specific representations of the human walk, which does not soften the context of vector images.
- It represents human motion in a single image while preserving temporal information.

Similarly, cross-view-based gait recognition is a popular approach used to deal with different visual angles. The input type requires multiple fully controlled cameras and cooperative environments, thus being restrained to real scenarios. Moreover, it visually normalizes gait characteristics before performing any combination, which allows the model to learn the relationships among visual movements in the scene [20, 109, 122]. An example of the approach can be observed in the UK's Newcastle University cross-view gait recognition system, the so-called DiGGAN, which obtained state-of-the-art results over the largest multiview gait dataset in the world [99] (comprising more than 10,000 people) using cross-view approaches [35].

Despite the success obtained by such methods, they still lack in some aspects, in which some less popular techniques aim to overcome. The Period Energy Image, for instance, comprises a multi-channel gait template proposed to tackle view angles' variation faced by cross-view and GEI loss of temporal information [28]. Another approach observed in some works comprises Optical-flow, which provides relevant information regarding the objects observed in the scene, their spatial arrangements, and the changes in such arrangements [57]. Finally, a wide range of hand-crafted features or sensor-based input data types is also employed for deep learning-based gait recognition approaches. Among such methods, one can find the Inertial Measurement Units, accelerometers, gyroscopes, sensor output, and so on.

Concerning gait recognition's actual state-of-the-art scenario, one can consider two main approaches, i.e., literature- and representation-based. Regarding the literature-based, 2D-CNNs are

the most widely used type of **deep neural network (DNN)** for gait recognition using deep learning, with approximately 50% of solutions just based on 2D-CNN architectures for classification. Solutions using 3D-CNN and GAN are the next popular categories, each corresponding to 10% of the published content. In addition, **deep autoencoder (DAE)**, RNN, CapsNet, DBN, and graph convolutional networks are less considered among DNNs, corresponding to 5%, 3%, 2%, 1%, and 1%, respectively. However, the hybrid methods constitute 26% of the solutions, in which the CNN-RNN combinations are the most widely adopted approach with about 15% of presence, while the combination of DAE with GAN and RNN corresponds to 10% of the methods, followed by the RNN-CapsNet methods that constitute 2% of the solutions.

Regarding state-of-the-art solutions based on representation, the silhouettes are the most widely adopted for gait recognition, corresponding to more than 85% of the solutions. Although it is a promising approach, skeletons have been considered less frequently in relation to silhouettes, corresponding to only 10% of the available solutions. There were also some methods, that is, approximately 5% of the available literature, that explore the representations of the skeleton and the silhouette, notably using unraveled representation learning or score of fusion strategies.

Considering deep learning-based gait recognition main challenges, one can refer to the complexity of gait data, which arises from the interaction between many factors, such as occlusion/obstruction, camera points of view, the appearance of individuals, order of sequence, movement of body parts, or light sources present in the data, among others [117, 129]. Such factors can interfere in a complicated way and can hinder the task of gait recognition. Currently, there is an increasing number of methods in other areas related to pattern recognition, such as face recognition, emotion, and pose estimation. These professionals focus on learning confusing contexts, extracting representations that separate the various explanatory factors in the data's high-dimensional space. However, most gait recognition methods available using deep learning have not yet explored such approaches. Therefore, they are not explicitly able to separate the underlying structure of gait data in the form of significant disjoint variables. Despite recent progress in using confusing context approaches in some gait recognition methods, there is still room for improvement.

4 DATASETS

Machine learning models' training and evaluation steps, regardless of the adopted paradigm, i.e., supervised, unsupervised, or any other, depend on a dataset comprising the task's subject. Besides, the employment of such datasets makes it possible to determine how effective a method is to solve a specific problem and compare it with other solutions.

Regarding gait recognition, the availability of specific datasets for the task is minimal, considering both public or private solutions. Such a lack of training data hampers the development of new artificial intelligence models capable of recognizing people by how they walk or move. Two problems stand out for obtaining and creating a dataset:

- Gait biometry demands a reasonable amount of movement recordings for a subject, implying recording and generating multiple videos for each individual. Besides, such videos usually possess an inherent high dimensionality, entailing in the dataset's growth and thus requiring a high storage capacity.
- The extraction and public distribution of biometric data require permission from each participant. The eventual creation of a dataset without formal consent from each individual may bring about lawsuits.

The next section gathers the most-used datasets available for gait-recognition-related tasks.

Table 2. Deep Learning-based Gait Recognition Approaches

Ref.	Year	Model	Input Type	Dataset	Result	Measure
[86]	2016	CNN	GEI	OU-ISIR	94.6%	Identification rate
[116]	2017	CNN	Cross-view	CASIA B	90.8%	Accuracy
[52]	2017	CNN + Joint Bayesian	Sensors	OU-ISR	97.6%	Identification rate
[90]	2017	CNN	Optical flow	TUM-GAID and CASIA B	97.52%	Accuracy
[98]	2017	CNN + Siamese networks	Cross-view	OU-ISIR	98.8%	Accuracy
[91]	2017	CNN + Nearest Neighbor	Optical Flow	TUM-GAID, CASIA B, and OU-ISIR	99.8%	Identification rate
[126]	2017	Autoencoders + PCA	GEI	CASIA B and SZU RGB	97.58%	Identification rate
[140]	2018	CNN + LSTM	Accelerometer and Gyroscope	whuGAIT and OU-ISIR	99.75%	Accuracy
[28]	2018	GAN	PEI	OU-ISIR, CASIA B and USF	94.7%	Accuracy
[21]	2018	DBN	Sensors	Data collected by the authors	93%	Accuracy
[121]	2019	Capsule	LBC and MMF	OU-ISIR	74.4%	Accuracy
[113]	2019	CNN	GEI + Data Augmentation	CASIA B	98%	Accuracy
[132]	2019	Autoencoders + LSTN	Cross- and Frontal-view	CASIA B, USF, and FVG	99.1%	Accuracy
[5]	2019	Autoencoders + PCA	GEI	OU-ISIR and CASIA B	96.15%	Accuracy
[76]	2019	LSTM	Sensors	Data collected by the authors	0.02	Prediction error
[41]	2019	GAN	GEI	CASIA A and CASIA B	82%	Recognition result
[115]	2020	LSTM	GEI	CASIA B and OU-ISIR	99.1%	Recognition rate
[119]	2020	CNN	Cross-view	OU-MVLP, OU-LP, and CASIA B	98.93%	Identification rate
[35]	2020	GAN	Cross-view	OU-MVLP and CASIA B	93.2%	Identification rate
[85]	2020	Capsule	Multi-scale representations	CASIA-B and OU-MVLP	84.5%	Identification rate
[118]	2020	DBN	Sensors	Data collected by the authors	2.61	RMSE
[103]	2021	LSTM	IMU	whuGAIT and OU-ISIR	94.15%	Accuracy
[133]	2021	Capsule	Sensors	Several	99.69%	Accuracy

Fig. 7. Examples of three male (top rows) and three female (bottom rows) participants in six variations: normal (columns 1 and 2), backpack (columns 3 and 4), coating shoes (columns 5 and 6), time (columns 7 and 8), time + backpack (columns 9 and 10), and time + coating shoes (columns 11 and 12). Extracted from <https://www.ei.tum.de/mmk/verschiedenes/tum-gaid-database/>.

4.1 CMU MoBo Dataset

The CMU MoBo [24] dataset possesses a relatively small amount of data, comprising several videos for gait recognition extracted from 20 people. The dataset also provides a set of silhouette masks and bounding boxes, thus alleviating the segmentation process.

One of the main advantages of the dataset is that it is available for download without reservations or need to sign forms of agreement, requiring just connecting to the Calgary University File Transfer Protocol (FTP) server.³

4.2 TUM GAID Dataset

The TUM **Gait from Audio, Image, and Depth (GAID)** [33] database, as the name suggests, is compounded by RGB images, audio, and depth, recorded from 305 people in three different variations at first. Further, 32 people were re-recorded to have some variation, comprising 3,370 records in total. According to the authors, it is the only dataset that allows recognition by combining video, depth, and audio.

Variations include different shows, carrying conditions (with and without bag), and time. The first record was performed in 2012's winter (January) and comprised 176 recordings, using a jacket and winter boots. The second performance was made in April 2012 by 161 people using considerably different clothes, since it was warmer. From this amount, 32 people were recorded both times, which grant cloth and time variation. A strong advantage of this dataset is a well-defined evaluation protocol. Figure 7 depicts some examples of images and depth. The dataset is available after signing a document request.⁴

4.3 HID-UMD Dataset

The **Human Identification at a Distance (HID)-UMD** dataset comprises several videos from people walking captured in four different angles and their respective binary masks for foreground segmentation. Its primary purpose is to help researchers develop new gait and facial biometrics

³<ftp://ftp.cc.gatech.edu/pub/gvu/cpl/>.

⁴<https://www.ei.tum.de/mmk/verschiedenes/tum-gaid-database/>.

Fig. 8. Example frames from CASIA A dataset from each angle. (a) corresponds to the parallel view, (b) corresponds to 90 degrees, and (c) is an example from 45 degrees. Images collected from http://www.cbsr.ia.ac.cn/users/szheng/?page_id=71.

recognition methods. Moreover, the dataset is an aggregate composed of two datasets, described as follows:

- **Dataset 1** [44]: composed of walking sequences of 25 individuals in four distinct poses:
 - (1) Frontal view/walking-toward;
 - (2) Frontal view/walking-away;
 - (3) Frontal-parallel view/toward left; and
 - (4) Frontal-parallel view/toward right.
- **Dataset 2** [12]: comprises videos from 55 individuals walking through a T-shape pathway. The sequences were obtained by two cameras that line orthogonal to each other.

More details can be found at <http://www.umiacs.umd.edu/labs/pirl/hid/umd-eval.html>. Further, the dataset is available to download through FTP, requiring credentials that can be requested at <http://www.umiacs.umd.edu/labs/pirl/hid/data.html>.

4.4 CASIA

The **Institute of Automation, Chinese Academy of Sciences (CASIA)** provides the CASIA Gait Database [136], a collection of four datasets designed for gait recognition purposes, and is described as follows:

- **CASIA A**: Created in December 2001 and formerly known as the NLPR Gait Database [114], the CASIA A dataset includes 20 individuals, each of them comprising 12 videos, i.e., 4 videos for each of the 3 directions, namely, parallel, 45, and 90 degrees to the image plane. Besides, each image sequence possesses its duration, varying with the individual walking velocity. Figure 8 shows some image examples from different angles. The dataset's total size is approximately 2.2 GB;
- **CASIA B**: Created in 2005, the CASIA B [127] comprises filming 124 individuals from 11 different angles. Each sequence was repeated three times, with variations such as clothing and walking speed. Moreover, the dataset also comprises a set of silhouettes provided for all sequences, provided for foreground segmentation. Figures 9 and 10 show variations in angle and clothing.
- **CASIA C**: Acquired in 2005, the CASIA C [100] dataset contains 153 subjects filmed by infrared cameras (thermal spectrum) in four different variations: normal walking, slow walking, fast walking, and normal walking carrying a backpack. Figure 11 shows some examples. All images were captured at night;
- **CASIA D**: The CASIA gait-footprint dataset [135] contains both images and cumulative foot pressure information. The dataset comprises 3,496 gait pose images and 2,658 cumulative

Fig. 9. Example frames from CASIA B dataset. Each image corresponds to one of the 11 comprised angles. Extracted from http://www.cbsr.ia.ac.cn/users/szheng/?page_id=71.

Fig. 10. Example frames from CASIA B dataset. One can notice the change in clothes and personal objects, like backpacks. Images collected from http://www.cbsr.ia.ac.cn/users/szheng/?page_id=71.

foot pressure images from 88 individuals with a broad distribution of age, 20 female and 68 male, in an indoor environment. Figure 12 illustrates the data acquisition schematics.

Silhouette for datasets A, B, and C are freely available for download.⁵ Regarding data acquisition, candidates should fill a form and wait for the dataset owner's approval.

4.5 OU-ISIR Biometric Database

The **Institute of Scientific and Industrial Research (ISIR)** of **Osaka University (OU)** has been creating, since 2007, the largest dataset for gait recognition in the world. The project is an aggregation of eight different groups:

- **Treadmill Dataset:** The group is composed of sequences from people walking on electronic treadmills surrounded by 25 cameras filming at 60 frames per second at a resolution of 640×480 . It has four subdivisions:
 - (1) **Treadmill dataset A – Speed variation [104]:** This subset comprises 34 subjects in a lateral vision with speed varying between 2 and 10km/h in 1km/h intervals;
 - (2) **Treadmill dataset B – Clothes variation [34]:** It is composed of 68 people in lateral vision with 32 clothing variations;

⁵<http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp>.

Fig. 11. Example frames from CASIA C dataset. The images were obtained through an infrared camera at night and with variations in the manner of walking. Adapted from http://www.cbsr.ia.ac.cn/users/szheng/?page_id=71.

Fig. 12. Example frames from CASIA D dataset. The images illustrate the images' acquisition process synchronously with the footsteps data. Images collected from http://www.cbsr.ia.ac.cn/users/szheng/?page_id=71.

- (3) **Treadmill dataset C – View variation** [60]: A large-scale database comprising 168 people with ages ranging from 4 to 75 years old. Moreover, the subset is composed of 25 views observed through a multi-view synchronous gait system;
 - (4) **Treadmill dataset D – Gait fluctuation** [66]: This set is composed of gait silhouette sequences with 185 subjects, viewed from a lateral angle and with variations in velocity. The data were subdivided into two groups of 100 subjects (with an overlap of 15 people) by high- and low-speed variations.
- **Large Population Dataset** [36]: Collected since 2009 through outreach activity events, the Large Population Dataset is composed of 4,016 subjects, each of them filmed twice from four camera angles at 30 FPS and a resolution of 640×480 pixels.
 - **Speed Transition Dataset** [61]: The Speed Transition Dataset comprises two subsets, described as follows:
 - (1) **Dataset A**: It contains 179 scenes from people walking at a constant velocity of 4km/h on a treadmill or the ground. In this set, the background has been removed using a wallpaper;
 - (2) **Dataset B**: It comprises sequences from 25 people walking on a treadmill with a velocity varying between 1 and 5km/h. Each person is filmed twice. Acceleration and deacceleration are performed in three seconds, and middle sequences with one second were extracted from both.

- **Multi-view Large Population Dataset [99]:** This dataset is composed of 10,307 samples such that 5,114 regard men and the remaining 5,193 stand for women, whose age ranges from 2 to 87 years, developed for motion recognition methods with cross-vision. The images were filmed in 14 different angles, at a frame rate of 25 frames per second, and a resolution of $1,280 \times 980$. The devices employed for capture were placed at a lateral distance and height of 8 and 5 meters, respectively.
- **Large Population Dataset with Bag [106]:** The dataset focuses on gait recognition concerning people carrying objects, aiming not only to rely on biometrics information but also on identifying the position of the transported part (if any) regarding the body. The Large Population Dataset with Bag comprises 62,528 people aged from 2 to 95 years obtained through a camera at a distance of approximately 8 meters and 5 meters height. The sequences were filmed at 25 frames per second with a resolution of $1,280 \times 980$ pixels. Each person was filmed three times, such that the first, i.e., A1, is carrying or not an object, while the second and third do not bring anything. Finally, a total of four regions are marked in case of something being carried, i.e., lower side, upper side, front, and back. All videos are also presented with a respective binary mask for background removal.
- **Large Population Dataset with Age [120]:** The Large Population Dataset with Age was created to investigate gait recognition concerning people's age and gender. The dataset comprises 62,846 individuals walking on a particular path with cameras capturing 640×480 pixels' resolution at a rate of 30 frames per second. The sequences' people are between 2 and 90 years old, and all videos have binary masks obtained after the background removal.
- **Inertial Sensor Dataset [68]:** Designated for research and evaluation of methods of individual identification by movements through motion sensors and accelerometers, the Inertial Sensor Dataset is the largest inertial sensor-based gait database, composed of images collected from 744 subjects (389 males and 355 females) whose ages range from 2 to 78 years.
- **Similar Actions Inertial Dataset [69]:** The Similar Actions Inertial Dataset comprises 460 participants aged between 8 and 78 with gender virtually equal distributed, whose walking properties were obtained together with the data presented in Reference [68]. Additionally, this dataset also presents six distinct characteristics of the floor: invalid, flat, stair climbing, stair climbing, ramp climbing, and ramp descent.

4.6 University of South Florida Dataset

The **University of South Florida (USF)** dataset [84] comprises 1,870 sequences from 122 subjects using two different shoe types. The dataset also considers individuals carrying or not carrying a briefcase, diverse surface conditions such as grass and concrete, and distinct camera views, i.e., left or right viewpoints. The videos are captured at two different time instants filmed in outdoor environments.

4.7 Southampton Dataset

The **Southampton Human ID at a Distance (SOTON)** database is a contribution of the University of Southampton composed of three major segments⁶:

- **SOTON Small database [70]:** Comprises 12 subjects walking around an inside track at varying speeds, wearing different shoes and clothes, and carrying or not carrying bags;

⁶More information available at http://www.eng.usf.edu/cvprg/Gait_Data.html.

Fig. 13. Example of the multiview dataset. The image presents people walking in different directions, from multiple points of view. Adapted from <https://www.uco.es/investiga/grupos/ava/node/41>.

- **SOTON Large database** [87]: Containing 114 subjects walking outside, inside on the laboratory track, and inside on a treadmill. Images were filmed from six different angles and provided in a collection with more than 5,000 sequences.
- **SOTON Temporal** [63]: The data was captured using a Multi-Biometric Tunnel, which contains 12 synchronized cameras to capture people's gait over time. The dataset is composed of dynamic environments, comprising distinct background, lighting, walking surface, and position of cameras. The dataset includes 25 subjects (17 male and 8 female) with ages ranging from 20 to 55 years old. Notice they are all filmed barefoot.

4.8 AVA Multi-view Dataset for Gait Recognition (AVAMVG)

The **AVA Multi-view Dataset for Gait Recognition (AVAMVG)**⁷ [14] is a database specifically designed for 3D-based gait recognition algorithms, which comprises gait images from 20 actors depicting different trajectories. The sequences were obtained using cameras specifically calibrated for the task, followed by a post-processing step using 3D image reconstruction algorithms. Besides, each sequence is also provided with a respective binary silhouette for segmentation. Finally, the database contains 200 six-channel multi-view videos that can also be employed as 1,200 single view videos, i.e., 6×200 . Figure 13 depicts some samples.

4.9 Kyushu University 4D Gait Database

The **Kyushu University 4D Gait Database (KY4D)**⁸ [38] is composed of sequential 3D models and image sequences of 42 subjects walking along four straight and two curved trajectories. The

⁷More information at: <http://www.uco.es/grupos/ava/node/41>.

⁸Available at <http://robotics.ait.kyushu-u.ac.jp/~yumi/db.html>.

Fig. 14. The studio from KY4D Gait Database A: (a) describes the trajectory indicated by the arrow and (b) depicts sequential 3D models of a person walking straight. Images adapted from http://robotics.ait.kyushu-u.ac.jp/~yumi/db/gait_b.html.

Fig. 15. The studio from KY4D Gait Database B: (a) describes the radius variation and (b) illustrates sequential 3D models of a person walking along a curved trajectory. Images adapted from http://robotics.ait.kyushu-u.ac.jp/~yumi/db/gait_b.html.

videos were recorded by 16 cameras, at a resolution of $1,032 \times 776$ pixels, and divided into three subsets, described as follows:

- **Dataset A (Straight):** It is composed of sequential 3D models and image sequences of people walking along straight trajectories. Figure 14(a) illustrates the trajectory, described as a red arrow. Figure 14(b) depicts multiple 3D reconstructed models.
- **Database B (Curve):** It comprises image sequences from people walking along curved trajectories, as depicted in Figure 15(a). The radius r varies either 1.5m or 3.0m. Figure 15(b) depicts multiple 3D reconstructed models considering the curve path.
- **KY Infrared (IR) Shadow Gait Database:** It is composed of time-series shadow images of 54 subjects. As indicated by the walking direction arrow in Figure 16(a), all people walk straight. Figure 16(b) depicts two infrared lights and a camera employed to collect the shadow database [37]. The infrared lights were placed obliquely, and the camera was placed on the ceiling perpendicular to the ground. A sample result from such captures is observed in Figure 17.

Fig. 16. (a) Experimental setting, (b) actual scene. Adapted from http://robotics.ait.kyushu-u.ac.jp/~yumi/db/gait_b.html.

Fig. 17. An example movie from IR shadow images. Image collected from http://robotics.ait.kyushu-u.ac.jp/~yumi/db/gait_b.html.

4.10 WhuGAIT Datasets

The whuGAIT Datasets [139] were released in 2018 by the Wuhan University and made available along with the source code and pre-trained models to replicate the paper results.⁹ Unlike other data collections, whuGAIT comprises 3D accelerometers and 3-axis gyroscope information collected from 118 people, 20 of them collected during three days, and 98 collected in just one day. The dataset is divided into six different subsets, according to the desired task:

- **Dataset #1:** Composed of 33,104 samples for training and 3,740 for testing from 118 individuals, divided into a two-step segmentation.
- **Dataset #2:** Similar to Dataset #1, comprises a two-step segmentation dataset composed of 49,275 samples for training and 4,936 for testing, extracted from the three days' collected data of 20 people.

⁹Available at <https://github.com/qinnzou/Gait-Recognition-Using-Smartphones>.

Table 3. Datasets in Usage Contexts

Context/Dataset	4.1	4.2	4.3	4.4	4.5	4.6	4.6	4.8	4.9	4.10
Viewpoint	x		x	x	x	x	x	x	x	x
Pace	x			x	x	x	x			x
Objects	x	x		x			x			
Shoe	x	x	x	x	x	x	x	x		
Clothing	x	x	x	x	x		x	x		
Time				x	x		x		x	x
Surface	x	x	x	x		x	x		x	x
Silhouette		x		x	x				x	
Gait Fluctuation					x					
Treadmill walking	x				x		x			
Overground walking	x	x	x	x		x		x	x	x
Foot pressure				x						

- **Dataset #3:** This subset is divided into time size windows, comprising 2.56 seconds for each sample. The set consists of 26,283 instances used for training and 2,991 employed for testing purposes.
- **Dataset #4:** Similar to Dataset #3, this subset is divided into time frames of 2.56 seconds, but using the data from 20 individuals collected during three days. The subset comprises 35,373 for training and 3,941 for testing purposes.
- **Dataset #5:** This subset is employed for authentication purposes. It is composed of 74,142 instances from 118 people, such that information extracted from 98 individuals is utilized for training, while the remaining 20 are used for validation. The authentication procedure is compounded by a pair of samples from one or two different subjects. The instances comprise two-step acceleration and gyroscopic data.
- **Dataset #6:** This subset employs the same structure used in Dataset #5, but instead of horizontal align, it uses vertical alignment.

4.11 Datasets in Usage Contexts

This section presented the datasets most commonly employed for gait recognition and used in the works considered in this survey. Thus, in the sequence, we also provide an overview regarding particular aspects, such as usage contexts, acquisition environments, and spectrum. Table 3 shows such information for each dataset. The covariates were divided into 12 main features, i.e., viewpoint, pace, objects, shoe, clothing, time, surface, silhouette, gait fluctuation, treadmill walking, overground walking, and foot pressure.

Further, Figure 18 presents the datasets' construction environments, which is divided into four scenarios, i.e., static indoor, static outdoor, active indoor, and active outdoor.

Finally, Figure 19 provides an illustrated schema categorizing the datasets' spectrum representation into two main classes, i.e., color-based and thermal information.

5 CONCLUSIONS AND FUTURE DIRECTIONS

This survey provided an in-depth research towards the most significant works developed in past years regarding gait recognition, highlighting deep learning techniques for such a task. Besides, it also provided a historical background concerning both methods for biometric identification, such as fingerprint, iris, and face, among others, as well as gait recognition, exposing the main concerns and challenges faced by the field.

Fig. 18. Representation of the dataset development environment.

Fig. 19. Data spectrum representation of the datasets.

Further, it provided a detailed description of the nine most-employed datasets for the task, i.e., CMU MoBo [24], TUM GAID [33], HID-UMD [12, 44], CASIA [100, 114, 127, 135], OU-ISIR [34, 36, 60, 61, 66, 68, 68, 99, 104, 106, 120], USF [84], SOTON [63, 70, 87], AVAMVG [14], KY4D [38], and WhuGait [139] as well as their extraction process and limitations. Regarding such datasets, one can clearly notice the efforts towards a detection independent from gender, angle in the scene, clothes and shoes, carry of bags and other items, among other common issues.

The works surveyed in this article discuss the main concerns and efforts made by the scientific community towards the development of techniques to guarantee access to monitored resources via gait identification and authorization. It also explores the advantages of a gait-based system against commonly employed biometric features, e.g., gait systems do not require the individuals' willingness to be identified. In this sense, the review attempted to point out the advantages of gait biometrics compared to other biometric techniques and highlight the most recent methodologies and state-of-the-art architectures.

There are a few critical points about video-based models and databases that are worth highlighting:

- The presented datasets do not introduce more than one person per video, either for training or validation purposes.
- The environments in which they were recorded are fully controlled. Despite the variation of angles in some sets, it is possible to notice no variation of objects or even of colors in the background. Other videos were recorded with people walking on electric treadmills, denoting even greater control of the movements and the environment.

- Consequently, the presented models cited in the work are probably prone to show lack and misbehavior when applied to the real-world operation, such as detecting people of interest walking on public streets.

Regarding future trends, we expect an increase in the number of works related to:

- (1) **Transformer networks:** The technique [107] targets data streaming such as video and fits the context of gait recognition perfectly.
- (2) **Gender and age recognition:** Such an approach [94] has gained popularity in past years due to its importance in several applications.
- (3) **Hazardous environment monitoring:** Gait features fit perfectly the purpose of monitoring hazardous environments, since they usually are composed of limited illumination, and extracting more descriptive biometric identification characteristics denotes a difficult task [83].
- (4) **Multiple people in the scene:** most of the gait recognition works focus on a single individual in the scene in controlled environments. However, real-life problems usually require solutions robust to non-controlled environments with multiple people in the scene.

Additionally, we observed an increasing demand for gait recognition on individuals with different clothes or carrying objects [126], as well as hybrid approaches composed of both gait and complementary biometric characteristics, such as face and ear [64].

REFERENCES

- [1] Ala Abdulhakim Alariki, Muqadas Faiz, Sanaullah Balagh, and Christine Murray. 2018. A review of finger-vein biometric recognition. In *Proceedings of the World Congress on Engineering and Computer Science*.
- [2] Abdullah S. Alharthi, Syed U. Yunus, and Krikor B. Ozanyan. 2019. Deep learning for monitoring of human gait: A review. *IEEE Sens. J.* 19, 21 (2019), 9575–9591.
- [3] Mohammad A. Alsmirat, Fatimah Al-Alem, Mahmoud Al-Ayyoub, Yaser Jararweh, and Brij Gupta. 2019. Impact of digital fingerprint image quality on the fingerprint recognition accuracy. *Multimedia Tools Applic.* 78, 3 (2019), 3649–3688.
- [4] P. Arora, M. Hanmandlu, and S. Srivastava. 2015. Gait based authentication using gait information image features. *Pattern Recog. Lett.* 68 (2015), 336–342.
- [5] Maryam Babaee, Linwei Li, and Gerhard Rigoll. 2019. Person identification from partial gait cycle using fully convolutional neural networks. *Neurocomputing* 338 (2019), 116–125.
- [6] Ruud M. Bolle, Jonathan H. Connell, Sharath Pankanti, Nalini K. Ratha, and Andrew W. Senior. 2013. *Guide to Biometrics*. Springer Science & Business Media.
- [7] Imed Bouchrika. 2018. A survey of using biometrics for smart visual surveillance: Gait recognition. In *Surveillance in Action*. Springer, 3–23.
- [8] Rung-Ching Chen, Christine Dewi, Wei-Wei Zhang, Jia-Ming Liu, Su-Wen Huang, et al. 2020. Integrating gesture control board and image recognition for gesture recognition based on deep learning. *Int. J. Appl. Sci. Eng.* 17, 3 (2020), 237–248.
- [9] Kyunghyun Cho, Bart Van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the properties of neural machine translation: Encoder-decoder approaches. *arXiv preprint arXiv:1409.1259* (2014).
- [10] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555* (2014).
- [11] Omar Costilla-Reyes, Ruben Vera-Rodriguez, Patricia Scully, and Krikor B. Ozanyan. 2018. Analysis of spatio-temporal representations for robust footstep recognition with deep residual neural networks. *IEEE Trans. Pattern Anal. Mach. Intell.* 41, 2 (2018), 285–296.
- [12] Naresh Cuntoor, Amit Kale, and Rama Chellappa. 2003. Combining multiple evidences for gait recognition. In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP'03)*. IEEE, III–33.
- [13] Shaveta Dargan and Munish Kumar. 2020. A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities. *Expert Syst. Applic.* 143 (2020), 113114.
- [14] David López-Fernández, Francisco J. Madrid-Cuevas, Ángel Carmona-Poyato, Manuel J. Marín-Jiménez, and Rafael Muñoz-Salinas. 2014. The AVA multi-view dataset for gait recognition. In *Activity Monitoring by Multiple Distributed Sensing*, Pier Luigi Mazzeo, Paolo Spagnolo, and Thomas B. Moeslund (Eds.). Springer International Publishing, 26–39. DOI: https://doi.org/10.1007/978-3-319-13323-2_3

- [15] Renato W. R. de Souza, Daniel S. Silva, Leandro A. Passos, Mateus Roder, Marcos C. Santana, Plácido R. Pinheiro, and Victor Hugo C. de Albuquerque. 2021. Computer-assisted Parkinson's disease diagnosis using fuzzy optimum-path forest and restricted Boltzmann machines. *Comput. Biol. Med.* 131 (2021), 104260.
- [16] Muqing Deng et al. 2018. Gait recognition under different clothing conditions via deterministic learning. *IEEE/CAA J. Automat. Sinica* (2018), 1–10.
- [17] Weihong Deng, Jiani Hu, and Jun Guo. 2018. Face recognition via collaborative representation: Its discriminant nature and superposed representation. *IEEE Trans. Pattern Anal. Mach. Intell.* 40, 10 (2018), 2513–2521.
- [18] Weihong Deng, Jiani Hu, Jiwen Lu, and Jun Guo. 2014. Transform-invariant PCA: A unified approach to fully automatic face alignment, representation, and recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* 36, 6 (2014), 1275–1284.
- [19] Christine Dewi and Rung-Ching Chen. 2019. Human activity recognition based on evolution of features selection and random Forest. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC'19)*. IEEE, 2496–2501.
- [20] G. Ariyanto and M. S. Nixon. 2011. Model-based 3D gait biometrics. *IJCB* (2011), 1–7.
- [21] Carlos Fernandes, Luís Fonseca, Flora Ferreira, Miguel Gago, Lus Costa, Nuno Sousa, Carlos Ferreira, Joao Gama, Wolfram Erlhagen, and Estela Bicho. 2018. Artificial neural networks classification of patients with Parkinsonism based on gait. In *Proceedings of the IEEE International Conference on Bioinformatics and Biomedicine (BIBM'18)*. IEEE, 2024–2030.
- [22] Vishwanath G. Garagad and Nalini C. Iyer. 2014. A novel technique of iris identification for biometric systems. In *Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI'14)*. IEEE, 973–978.
- [23] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial networks. *arXiv preprint arXiv:1406.2661* (2014).
- [24] Ralph Gross and Jianbo Shi. 2001. *The CMU Motion of Body (MoBo) Database*. Technical Report CMU-RI-TR-01-18. Carnegie Mellon University.
- [25] Qiong Gui, Maria V. Ruiz-Blondet, Sarah Laszlo, and Zhanpeng Jin. 2019. A survey on brain biometrics. *ACM Comput. Surv.* 51, 6 (2019), 1–38.
- [26] Ju Han and Bir Bhanu. 2016. Individual recognition using gait energy image. *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE* (2016).
- [27] Jing Selena He, Mingyuan Yan, and Sahil Arora. 2020. Long range iris recognition a reality or a myth? A survey. In *Proceedings of the ACM Southeast Conference*. 305–306.
- [28] Yiwei He, Junping Zhang, Hongming Shan, and Liang Wang. 2018. Multi-task GANs for view-specific feature learning in gait recognition. *IEEE Transactions on Information Forensics and Security* 14, 1 (2018), 102–113.
- [29] S. Hemalatha. 2020. A systematic review on fingerprint based biometric authentication system. In *Proceedings of the International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE'20)*. IEEE, 1–4.
- [30] G. E. Hinton. 2002. Training products of experts by minimizing contrastive divergence. *Neural Comput.* 14, 8 (2002), 1771–1800.
- [31] G. E. Hinton, S. Osindero, and Y.-W. Teh. 2006. A fast learning algorithm for deep belief nets. *Neural Comput.* 18, 7 (2006), 1527–1554.
- [32] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Comput.* 9, 8 (1997), 1735–1780.
- [33] Martin Hofmann, Jürgen Geiger, Sebastian Bachmann, Björn Schuller, and Gerhard Rigoll. 2014. The TUM gait from audio, image and depth (gaid) database: Multimodal recognition of subjects and traits. *J. Vis. Commun. Image Represent.* 25, 1 (2014), 195–206.
- [34] Md Altab Hossain, Yasushi Makihara, Junqiu Wang, and Yasushi Yagi. 2010. Clothing-invariant gait identification using part-based clothing categorization and adaptive weight control. *Pattern Recog.* 43, 6 (2010), 2281–2291.
- [35] BingZhang Hu, Yu Guan, Yan Gao, Yang Long, Nicholas Lane, and Thomas Ploetz. 2018. Robust cross-view gait recognition with evidence: A discriminant gait GAN (DiGGAN) approach. *arXiv preprint arXiv:1811.10493* (2018).
- [36] H. Iwama, M. Okumura, Y. Makihara, and Y. Yagi. 2012. The OU-ISIR gait database comprising the large population dataset and performance evaluation of gait recognition. *IEEE Trans. Inf. Forens. Secur.* 7, 5 (Oct. 2012), 1511–1521.
- [37] Y. Iwashita, R. Kurazume, and A. Stoica. 2014. Gait identification using invisible shadows: Robustness to appearance changes. In *Proceedings of the International Conference on Emerging Security Technologies (EST'14)*. UK.
- [38] Y. Iwashita, K. Ogawara, and R. Kurazume. 2014. Identification of people walking along curved trajectories. In *Pattern Recog. Lett.*
- [39] Anil K. Jain et al. 2004. An introduction to biometric recognition. In *IEEE Transactions on Circuits and Systems for Video Technology, Special Issue on Image- and Video-Based Biometrics, Vol. 14, No. 1* (2004).
- [40] Umarani Jayaraman, Phalguni Gupta, Sandesh Gupta, Geetika Arora, and Kamlesh Tiwari. 2020. Recent development in face recognition. *Neurocomputing* 408 (2020), 231–245.
- [41] Meijuan Jia, Hongyu Yang, Di Huang, and Yunhong Wang. 2019. Attacking gait recognition systems via silhouette guided GANs. In *Proceedings of the 27th ACM International Conference on Multimedia*. 638–646.

- [42] Chunyuan Zi, Ying Niu, Huixin Tian, Jing Luo, Jianliang Zhang, and Chunbo Xiu. 2015. Gait recognition using GEI and AFDEL. *Int. J. Optics* (2015).
- [43] K. Jun, D. Lee, K. Lee, S. Lee, and M. S. Kim. 2020. Feature extraction using an RNN autoencoder for skeleton-based abnormal gait recognition. *IEEE Access* 8 (2020), 19196–19207.
- [44] Amit Kale, Naresh Cuntoor, and Rama Chellappa. 2002. A framework for activity-specific human identification. In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*. IEEE, IV–3660.
- [45] Meina Kan, Shiguang Shan, Hong Chang, and Xilin Chen. 2014. Stacked progressive auto-encoders (SPA-E) for face recognition across poses. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 1883–1890.
- [46] Pradeep Karn, XiaoHai He, Jin Zhang, and Yanteng Zhang. 2020. An experimental study of relative total variation and probabilistic collaborative representation for iris recognition. *Multim. Tools. Applic.* 79, 43 (2020), 31783–31801.
- [47] Saad Khan, Simon Parkinson, Liam Grant, Na Liu, and Stephen Mcguire. 2020. Biometric systems utilising health data from wearable devices: Applications and future challenges in computer security. *ACM Comput. Surv.* 53, 4 (2020), 1–29.
- [48] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. 2012. Imagenet classification with deep convolutional neural networks. In *Proceedings of the International Conference on Advances in Neural Information Processing Systems*. 1097–1105.
- [49] Yann LeCun, Léon Bottou, Yoshua Bengio, Patrick Haffner, et al. 1998. Gradient-based learning applied to document recognition. *Proc. IEEE* 86, 11 (1998), 2278–2324.
- [50] Wonjune Lee, Sungchul Cho, Heeseung Choi, and Jaihie Kim. 2017. Partial fingerprint matching using minutiae and ridge shape features for small fingerprint scanners. *Exp. Syst. Applic.* 87, C (2017), 183–198.
- [51] Zhen Lei, Matti Pietikäinen, and Stan Z. Li. 2014. Learning discriminant face descriptor. *IEEE Trans. Pattern Anal. Mach. Intell.* 36, 2 (2014), 289–302.
- [52] C. Li, X. Min, S. Sun, W. Lin, and Z. Tang. 2017. DeepGait: A learning deep convolutional representation for view-invariant gait recognition using joint Bayesian. *Appl. Sci.* 7, 3 (2017), 210.
- [53] Shuyi Li, Bob Zhang, Lunke Fei, and Shuping Zhao. 2021. Joint discriminative feature learning for multimodal finger recognition. *Pattern Recog.* 111 (2021), 107704.
- [54] Stan Z. Li. 2009. *Encyclopedia of Biometrics: I–Z*. Vol. 2. Springer Science & Business Media.
- [55] V. C. Lobo, L. A. Passos, and J. P. Papa. 2020. Evolving long short-term memory networks. In *Proceedings of the International Conference on Computational Science (ICCS’20)*. IEEE.
- [56] Jian Luo and Tardi Tjahjadi. 2020. Multi-set canonical correlation analysis for 3D abnormal gait behaviour recognition based on virtual sample generation. *IEEE Access* 8 (2020), 32485–32501.
- [57] Zhengping Luo, Tianqi Yang, and Yanjun Liu. 2016. Gait optical flow image decomposition for human recognition. In *Proceedings of the IEEE Information Technology, Networking, Electronic and Automation Control Conference*. IEEE, 581–586.
- [58] Zhuo Ma, Yilong Yang, Ximeng Liu, Yang Liu, Siqi Ma, Kui Ren, and Chang Yao. 2019. Emir-Auth: Eye-movement and iris based portable remote authentication for smart grid. *IEEE Trans. Industr. Inform.* 16, 10 (2019), 6597–6606.
- [59] Y. Makihara, H. Mannami, A. Tsuji, M. A. Hossain, K. Sugiura, A. Mori, and Y. Yagi. 2012. The OU-ISIR gait database comprising the treadmill dataset. *IPSP Trans. Comput. Vis. Applic.* 4 (Apr. 2012), 53–62.
- [60] Yasushi Makihara, Hidetoshi Mannami, and Yasushi Yagi. 2010. Gait analysis of gender and age using a large-scale multi-view gait database. In *Proceedings of the Asian Conference on Computer Vision*. Springer, 440–451.
- [61] Al Mansur, Yasushi Makihara, Rasyid Aqmar, and Yasushi Yagi. 2014. Gait recognition under speed transition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2521–2528.
- [62] Maria De Marsico and Alessio Mecca. 2019. A survey on gait recognition via wearable sensors. *ACM Comput. Surv.* 52, 4 (2019), 1–39.
- [63] Darko S. Matovski, Mark S. Nixon, Sasan Mahmoodi, and John N. Carter. 2010. The effect of time on the performance of gait biometrics. In *Proceedings of the 4th IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS’10)*. IEEE, 1–6.
- [64] Haider Mehraj and Ajaz Hussain Mir. 2020. Feature vector extraction and optimisation for multimodal biometrics employing face, ear and gait utilising artificial neural networks. *Int. J. Cloud Comput.* 9, 2–3 (2020), 131–149.
- [65] C. Ainsworth Mitchell. 1920. The detection of finger-prints on documents. *Analyst* 45, 529 (1920), 122–129.
- [66] Atsushi Mori, Yasushi Makihara, and Yasushi Yagi. 2010. Gait recognition using period-based phase synchronization for low frame-rate videos. In *Proceedings of the 20th International Conference on Pattern Recognition*. IEEE, 2194–2197.
- [67] Athira Nambiar, Alexandre Bernardino, and Jacinto C. Nascimento. 2019. Gait-based person re-identification: A survey. *ACM Comput. Surv.* 52, 2 (2019), 1–34.
- [68] Thanh Trung Ngo, Yasushi Makihara, Hajime Nagahara, Yasuhiro Mukaigawa, and Yasushi Yagi. 2014. The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication. *Pattern Recog.* 47, 1 (2014), 228–237.

- [69] Trung Thanh Ngo, Yasushi Makihara, Hajime Nagahara, Yasuhiro Mukaigawa, and Yasushi Yagi. 2015. Similar gait action recognition using an inertial sensor. *Pattern Recog.* 48, 4 (2015), 1289–1301.
- [70] M. Nixon, J. Carter, J. Shutler, and M. Grant. 2001. Experimental plan for automatic gait recognition. *University of Southampton, Southampton, UK* (2001).
- [71] Mark S. Nixon and John N. Carter. 2004. Advances in automatic gait recognition. In *Proceedings of the Sixth IEEE International Conference on Automatic Face and Gesture Recognition*. 139–144.
- [72] Alan V. Oppenheim, John R. Buck, and Ronald W. Schaffer. 2001. *Discrete-time Signal Processing*. Vol. 2. Prentice Hall, Upper Saddle River, NJ.
- [73] Leandro A. Passos, Kelton A. P. Costa, and João P. Papa. 2017. Deep Boltzmann machines using adaptive temperatures. In *Proceedings of the International Conference on Computer Analysis of Images and Patterns*. Springer, 172–183.
- [74] L. A. Passos, M. C. Santana, T. Moreira, and J. P. Papa. 2019. κ -entropy based restricted Boltzmann machines. In *Proceedings of the International Joint Conference on Neural Networks (IJCNN'19)*. IEEE, 1–8.
- [75] Paulo Henrique Pisani, Abir Mhenni, Romain Giot, Estelle Cherrier, Norman Poh, André Carlos Ponce de Leon Ferreira de Carvalho, Christophe Rosenberger, and Najoua Essoukri Ben Amara. 2019. Adaptive biometric systems: Review and perspectives. *ACM Comput. Surv.* 52, 5 (2019), 1–38.
- [76] Sasanka Potluri, Srinivas Ravuri, Christian Diedrich, and Lutz Schega. 2019. Deep learning based gait abnormality detection using wearable sensor system. In *Proceedings of the 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'19)*. IEEE, 3613–3619.
- [77] Elizabeth J. Ragan, Courtney Johnson, Jacqueline N. Milton, and Christopher J. Gill. 2016. Ear biometrics for patient identification in global health: A cross-sectional study to test the feasibility of a simplified algorithm. *BMC Res. Notes* 9, 1 (2016).
- [78] D. A. Ramli, M. Y. Hooi, and K. J. Chee. 2016. Development of heartbeat detection kit for biometric authentication system. *Procedia Comput. Sci.* 96 (2016), 305–314.
- [79] Imad Rida, Noor Almaadeed, and Somaya Almaadeed. 2018. Robust gait recognition: A comprehensive survey. *IET Biomet.* 8, 1 (2018), 14–28.
- [80] I. Rida, X. Jiang, and G. L. Marcalis. 2016. Human body part selection by group lasso of motion for model-free gait recognition. *IEEE Sig. Process. Lett.* 23, 1 (2016), 154–158.
- [81] M. Roder, L. A. Passos, L. C. F. Ribeiro, B. C. Benato, A. L. Falcão, and J. P. Papa. In Press. Intestinal parasites classification using deep belief networks. In *Proceedings of the 19th International Conference on Artificial Intelligence and Soft Computing (ICAISC)*. IEEE, 242–251.
- [82] Sara Sabour, Nicholas Frosst, and Geoffrey E. Hinton. 2017. Dynamic routing between capsules. In *Proceedings of the International Conference on Advances in Neural Information Processing Systems*. 3856–3866.
- [83] Marcos C. Santana, Leandro A. Passos, Thierry P. Moreira, Danilo Colombo, Victor Hugo C. de Albuquerque, and João P. Papa. 2019. A novel siamese-based approach for scene change detection with applications to obstructed routes in hazardous environments. *IEEE Intell. Syst.* 35, 1 (2019), 44–53.
- [84] Sudeep Sarkar, P. Jonathon Phillips, Zongyi Liu, Isidro Robledo Vega, Patrick Grother, and Kevin W. Bowyer. 2005. The humanID gait challenge problem: Data sets, performance, and analysis. *IEEE Trans. Pattern Anal. Mach. Intell.* 27, 2 (2005), 162–177.
- [85] Alireza Sepas-Moghaddam, Saeed Ghorbani, Nikolaus F. Troje, and Ali Etemad. 2021. Gait recognition using multi-scale partial representation transformation with capsules. In *Proceedings of the 25th International Conference on Pattern Recognition (ICPR'20)*. IEEE, 8045–8052.
- [86] Kohei Shiraga, Yasushi Makihara, Daigo Muramatsu, Tomio Echigo, and Yasushi Yagi. 2016. GEINET: View-invariant gait recognition using a convolutional neural network. In *Proceedings of the International Conference on Biometrics (ICB'16)*. IEEE, 1–8.
- [87] Jamie D. Shutler, Michael G. Grant, Mark S. Nixon, and John N. Carter. 2004. On a large sequence-based human gait database. In *Applications and Science in Soft Computing*. Springer, 339–346.
- [88] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).
- [89] Jasvinder Pal Singh, Sanjeev Jain, Sakshi Arora, and Uday Pratap Singh. 2018. Vision-based gait recognition: A survey. *IEEE Access* 6 (2018), 70497–70527.
- [90] A. Sokolova and A. Konushin. 2017. Gait recognition based on convolutional neural networks. *Int. Arch. Photogramm. Rem. Sens. Spatial Inf. Sci.* 42 (2017).
- [91] Anna Sokolova and Anton Konushin. 2017. Pose-based deep gait recognition. *CoRR* abs/1710.06512 (2017).
- [92] Luis A. Souza Jr, Leandro A. Passos, Robert Mendel, Alanna Ebigbo, Andreas Probst, Helmut Messmann, Christoph Palm, and João P. Papa. 2020. Assisting Barrett's esophagus identification using endoscopic data augmentation based on generative adversarial networks. *Comput. Biol. Med.* 126 (2020), 104029.

- [93] Madeena Sultana, Padma Polash Paul, and Marina L. Gavrilova. 2017. Social behavioral information fusion in multi-modal biometrics. *IEEE Trans. Syst. Man Cybern.: Syst.* 48, 12 (2017), 2176–2187.
- [94] Yingnan Sun, Frank P.-W. Lo, and Benny Lo. 2019. A deep learning approach on gender and age recognition using a single inertial sensor. In *Proceedings of the IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN'19)*. IEEE, 1–4.
- [95] Aditya Sundararajan, Arif I. Sarwat, and Alexander Pons. 2019. A survey on modality characteristics, performance evaluation metrics, and security for traditional and wearable biometric systems. *ACM Comput. Surv.* 52, 2 (2019), 1–36.
- [96] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2818–2826.
- [97] Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. 2014. DeepFace: Closing the gap to human-level performance in face verification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 1701–1708.
- [98] Noriko Takemura, Yasushi Makihara, Daigo Muramatsu, Tomio Echigo, and Yasushi Yagi. 2017. On input/output architectures for convolutional neural network-based cross-view gait recognition. *IEEE Trans. Circ. Syst. Vid. Technol.* 29, 9 (2017), 2708–2719.
- [99] Noriko Takemura, Yasushi Makihara, Daigo Muramatsu, Tomio Echigo, and Yasushi Yagi. 2018. Multi-view large population gait dataset and its performance evaluation for cross-view gait recognition. *IPSJ Trans. Comput. Vis. Applic.* 10, 1 (2018), 4.
- [100] Daoliang Tan, Kaiqi Huang, Shiqi Yu, and Tieniu Tan. 2006. Efficient night gait recognition based on template matching. In *Proceedings of the 18th International Conference on Pattern Recognition (ICPR'06)*. IEEE, 1000–1003.
- [101] Mingxing Tan and Quoc Le. 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the International Conference on Machine Learning*. PMLR, 6105–6114.
- [102] Leslie Ching, Ow Tiong, Seong Tae Kim, and Yong Man Ro. 2020. Multimodal facial biometrics recognition: Dual-stream convolutional neural networks with multi-feature fusion layers. *Image Vis. Comput.* 102 (2020), 103977.
- [103] Lam Tran, Thang Hoang, Thuc Nguyen, Hyunil Kim, and Deokjai Choi. 2021. Multi-model long short-term memory network for gait recognition using window-based data segment. *IEEE Access* 9 (2021), 23826–23839.
- [104] Akira Tsuji, Yasushi Makihara, and Yasushi Yagi. 2010. Silhouette transformation based on walking speed for gait identification. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE, 717–722.
- [105] Matthew Turk and Alex Pentland. 1991. Eigenfaces for recognition. *J. Cog. Neurosci.* 3, 1 (1991), 71–86.
- [106] Md Zasim Uddin, Thanh Trung Ngo, Yasushi Makihara, Noriko Takemura, Xiang Li, Daigo Muramatsu, and Yasushi Yagi. 2018. The OU-ISIR large population gait database with real-life carried object and its performance evaluation. *IPSJ Trans. Comput. Vis. Applic.* 10, 1 (2018), 1–11.
- [107] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762* (2017).
- [108] Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, Pierre-Antoine Manzagol, and Léon Bottou. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *J. Mach. Learn. Res.* 11, 12 (2010).
- [109] Jian Zhang, Yi Ma, W. Kusakunniran, Qiang Wu, and Hongdong Li. 2013. A new view-invariant feature for cross-view gait recognition. *IEEE TIFS* 8, 10 (2013), 1642–1653.
- [110] Changsheng Wan, Li Wang, and Vir V. Phoha. 2018. A survey on gait recognition. *ACM Comput. Surv.* 51, 5 (2018), 1–35.
- [111] Caiyong Wang, Jawad Muhammad, Yunlong Wang, Zhaofeng He, and Zhenan Sun. 2020. Towards complete and accurate iris segmentation using deep multi-task attention network for non-cooperative iris recognition. *IEEE Trans. Inf. Forens. Secur.* 15 (2020), 2944–2959.
- [112] Kuo Wang and Ajay Kumar. 2019. Cross-spectral iris recognition using CNN and supervised discrete hashing. *Pattern Recog.* 86 (2019), 85–98.
- [113] Kejun Wang, Liangliang Liu, Yilong Lee, Xinnan Ding, and Junyu Lin. 2019. Nonstandard periodic gait energy image for gait recognition and data augmentation. In *Proceedings of the Chinese Conference on Pattern Recognition and Computer Vision (PRCV'19)*. Springer, 197–208.
- [114] Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. 2003. Silhouette analysis-based gait recognition for human identification. *IEEE Trans. Pattern Anal. Mach. Intell.* 25, 12 (2003), 1505–1518.
- [115] Xiuhui Wang and Wei Qi Yan. 2020. Human gait recognition based on frame-by-frame gait energy images and convolutional long short-term memory. *Int. J. Neural Syst.* 30, 01 (2020), 1950027.

- [116] Zifeng Wu, Yongzhen Huang, Liang Wang, Xiaogang Wang, and Tieniu Tan. 2017. A comprehensive study on cross-view gait based human identification with deep CNNs. *IEEE Trans. Pattern Anal. Mach. Intell.* 39, 2 (2017), 209–226.
- [117] C. Xu, Y. Yagi, X. Li, Y. Makihara, and M. Ren. 2020. Gait recognition via semi-supervised disentangled representation learning to identity and covariate features. *Comput. Vis. Pattern Recog.* (2020), 13306–13316.
- [118] Dezhen Xiong, Daohui Zhang, Xingang Zhao, and Yiwen Zhao. 2020. Continuous human gait tracking using sEMG signals. In *Proceedings of the 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC'20)*. IEEE, 3094–3097.
- [119] Chi Xu, Yasushi Makihara, Xiang Li, Yasushi Yagi, and Jianfeng Lu. 2020. Cross-view gait recognition using pairwise spatial transformer networks. *IEEE Trans. Circ. Syst. Vid. Technol.* 31, 1 (2020), 260–274.
- [120] Chi Xu, Yasushi Makihara, Gakuto Ogi, Xiang Li, Yasushi Yagi, and Jianfeng Lu. 2017. The OU-ISIR gait database comprising the large population dataset with age and performance evaluation of age estimation. *IPSJ Trans. Comput. Vis. Applic.* 9, 24 (2017), 1–14.
- [121] Zhaopeng Xu, Wei Lu, Qin Zhang, Yuileong Yeung, and Xin Chen. 2019. Gait recognition based on capsule network. *J. Vis. Commun. Image Represent.* 59 (2019), 159–167.
- [122] Yasuhiro Mukaigawa, Tomio Echigo, Yasushi Makihara, Ryusuke Sagawa, and Yasushi Yagi. 2006. Gait recognition using a view transformation model in the frequency domain. In *ECCV: v.3953* (2006), 151–163.
- [123] Sang Seok Yeo and Ga Young Park. 2020. Accuracy verification of spatio-temporal and kinematic parameters for gait using inertial measurement unit system. *Sensors* 20, 5 (2020).
- [124] P. Yogarajah, P. Chaurasia, J. Condell, and G. Prasad. 2015. Enhancing gait based person identification using joint sparsity model and -norm minimization. *Pattern Recog.* 38 (2015), 3–22.
- [125] Ning Yu, Larry S. Davis, and Mario Fritz. 2019. Attributing fake images to GANs: Learning and analyzing GAN fingerprints. In *Proceedings of the IEEE International Conference on Computer Vision*. 7556–7566.
- [126] Shiqi Yu, Haifeng Chen, Qing Wang, Linlin Shen, and Yongzhen Huang. 2017. Invariant feature extraction for gait recognition using only one uniform model. *Neurocomputing* 239 (2017), 81–93.
- [127] Shiqi Yu, Daoliang Tan, and Tieniu Tan. 2006. A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition. *Pattern Recog.* 4 (2006), 441–444. DOI: <https://doi.org/10.1109/ICPR.2006.67>
- [128] Shiqi Yu, Qing Wang, and Yongzhen Huang. 2013. A large RGB-D gait dataset and the baseline algorithm. In *Proceedings of the Chinese Conference on Biometric Recognition*. Springer, 417–424.
- [129] F. Liu, Z. Zhang, L. Tran, and X. Liu. 2020. On learning disentangled representations for gait recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* (2020).
- [130] Sergey Zagoruyko and Nikos Komodakis. 2016. Wide residual networks. *arXiv preprint arXiv:1605.07146* (2016).
- [131] Niv Zehngut, Felix Juefei-Xu, Rishabh Bardia, Dipan K. Pal, Chandrasekhar Bhagavatula, and Marios Savvides. 2015. Investigating the feasibility of image-based nose biometrics. In *Proceedings of the IEEE International Conference on Image Processing (ICIP'15)*. IEEE, 522–526.
- [132] Ziyuan Zhang, Luan Tran, Xi Yin, Yousef Atoum, Xiaoming Liu, Jian Wan, and Nanxin Wang. 2019. Gait recognition via disentangled representation learning. *arXiv preprint arXiv:1904.04925* (2019).
- [133] Aite Zhao, Junyu Dong, Jianbo Li, Lin Qi, and Huiyu Zhou. 2021. Associated spatio-temporal capsule network for gait recognition. *arXiv preprint arXiv:2101.02458* (2021).
- [134] X. Zhao, Y. Jiang, T. Stathaki, and H. Zhang. 2016. Gait recognition method for arbitrary straight walking paths using appearance conversion machine. *Neurocomputing* 173 (2016), 530–540.
- [135] Shuai Zheng, Kaiqi Huang, Tieniu Tan, and Dacheng Tao. 2012. A cascade fusion scheme for gait and cumulative foot pressure image recognition. *Pattern Recog.* 45, 10 (2012), 3603–3610.
- [136] Shuai Zheng, Junge Zhang, Kaiqi Huang, Ran He, and Tieniu Tan. 2011. Robust view transformation model for gait recognition. In *Proceedings of the 18th IEEE International Conference on Image Processing*. IEEE, 2073–2076.
- [137] R. Abu Zneit, Ziad AlQadi, and M. Abu Zalata. 2017. A methodology to create a fingerprint for RGB color image. *Int. J. Comput. Sci. Mob. Comput.* 16, 1 (2017), 205–212.
- [138] Barret Zoph, Golnaz Ghiasi, Tsung-Yi Lin, Yin Cui, Hanxiao Liu, Ekin D. Cubuk, and Quoc V. Le. 2020. Rethinking pre-training and self-training. *arXiv preprint arXiv:2006.06882* (2020).
- [139] Qin Zou, Yanling Wang, Yi Zhao, Qian Wang, Chao Shen, and Qingquan Li. 2018. Deep learning based gait recognition using smartphones in the wild. *CoRR abs/1811.00338* (2018).
- [140] Qin Zou, Yanling Wang, Yi Zhao, Qian Wang, Chao Shen, and Qingquan Li. 2018. Deep learning based gait recognition using smartphones in the wild. *arXiv preprint arXiv:1811.00338* (2018).

Received December 2020; revised June 2021; accepted September 2021