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Gait recognition methods in the task of biometric human identification

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ABSTRACT

This article focuses on defining the problem of solving the problem of human identification by means of gait recognition in biometric identification systems. In order to determine the prospects of using gait recognition methods for human identification, a generalized model of a biometric identification system was considered, the main modules of the system were identified and a brief description of each module was provided. Next, the basic requirements for human biometric features were identified, the main biometric features were considered, and the features of their use in biometric identification systems were determined. The issue of using gait as a biometric identifier was also considered. It has been determined that the use of human gait allows to get rid of two main obstacles in the construction of biometric identification systems: users are not required to provide personal biometric information in advance, and the system does not require specialized equipment. Also, the issue of multi-view gait recognition was considered. Multi-view gait recognition involves capturing gait data from different angles and using this data to improve recognition accuracy. This approach has shown great promise in challenging scenarios such as low lighting conditions. Next, we analyzed scientific works in the field of gait recognition. It was determined that gait recognition methods can be divided into template-based and non-template-based methods. Template-based methods are aimed at obtaining patterns of torso or leg movements, i.e. they usually focus on the dynamics of movement in space or on spatio-temporal methods. Non-template-based methods consider shape and its features as more relevant characteristics, i.e., human recognition are performed using measurements that reflect the shape of the person. Next, we consider the use of different datasets in the process of training and testing human gait recognition methods. The main datasets were identified and their characteristics and features were collected. We considered the presence of various characteristics in the datasets, as well as the means of representing information about human gait. The research has identified the main problems and challenges facing researchers in this area, as well as the main trends in the field of human gait recognition in biometric identification systems.

Keywords: Biometric identification; neural networks; pattern recognition; datasets; deep learning; convolution neural networks, computer vision

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INTRODUCTION, FORMULATION OF THE PROBLEM

The desire to differentiate and identify various persons has grown as human civilization has developed. The performance of computers has significantly increased over the past several decades due to the fast growth of information technology, and evermore complicated recognition scenarios have been suggested, which has accelerated the development of recognition and identification systems [1].

Biometric traits, such as height, weight, and face, are often the most reliable ways to identify someone since they do not vary much over time.

Biometric features can successfully prevent these drawbacks. Recognition systems based on other characteristics', such as keys and passwords, are also useful, but there are drawbacks like losing keys and forgetting passwords. A number of biometric traits, including voice, hand, fingerprint, iris, face, and even DNA, have been employed as human attributes for identification since the 1960s thanks to significant advancements in digital signal processing [2].

For a candidate characteristic to be deemed a biometric qualifying criterion, it must satisfy the following conditions [3]:

– universality – every individual must possess this feature;

– uniqueness – any two individuals must differ significantly in terms of the trait;

– permanence – the trait must remain mostly intact through time;

– collectability – the trait may be quantified.

In the practical application of biometric systems, however, other issues must be considered, including:

– performance – the ability to quickly recognize a trait with achievable accuracy, the amount of resources required to achieve the desired accuracy and speed of recognition, and operational and environmental factors that may affect accuracy and speed;

– acceptability – the degree to which people are willing to accept the use of a particular biometric identifier in a given context;

– privacy – how hard it is to trick the system with fake information [3].

Although the reliability and security of common biometric identification methods is confirmed by their successful application in banks and public administration systems, two main obstacles to the use of these systems should be emphasized: they depend on the prior provision of personal biometric information (i.e., the person must provide or register the necessary information for recognition), and they require specialized equipment [4]

An alternative approach that does not have the aforementioned drawbacks is gait-based human identification models (especially when it comes to approaches based on video surveillance systems). This approach does not suffer from the above-mentioned problems, since obtaining biometric information depends, in most cases, only on a regular camera, without the need to use sensors or other devices [5].

In addition, the collection of such biometric information is carried out in a passive mode (the legal aspects of collecting such information are not considered in this paper). Thus, the successful functioning of such systems does not require cooperation or provision of any information from the monitored persons [6].

Thus, **the purpose of this research** is to determine the prospects of using gait as a biometric feature in biometric identification systems. To achieve this goal, it is necessary to consider a generalized model of a biometric identification system and conduct a scientific analysis of works in the field of gait recognition, identify the main obstacles and trends in this area.

1. GENERAL BIOMETRIC IDENTIFICATION SYSTEM MODEL

A broad explanation of a biometric identification system (BIS) is required for comprehending biometric identification technologies and comparing systems that seem to be dissimilar.

Despite the fact that other generalized models may be offered, a really universal model is preferred over taxonomies or splitting systems into distinct phases. James L. Wayman suggested such a model; illustrating a system diagram with five distinct subsystems that may be deemed independent at first glance [7] (Fig. 1). Below is a full description of each subsystem.

The subsystem for collecting data. This component is liable for capturing the biometric characteristic to be examined. The biometric trait must be distinguishable and consistent throughout time. The biometric characteristic is supplied to the sensor for data gathering. Often, a preset presentation is required (such as putting a fingertip on a sensor while applying mild pressure).

While creating a biometric identification system, the degree of user involvement necessary and the context in which data collection will occur must be considered in order to create as little variance as feasible in the data collecting phase.

The transmission subsystem. In many instances, the collecting and processing of biometric data occur at separate sites. Hence, some kind of transmission is necessary. Moreover, data compression may be necessary to reduce transmission bandwidth.

Many distinct situations involving data transfer come to mind:

– data are gathered at one site and then transferred to another for processing (feature extraction, storage, decision making, etc.). There are compression standards for fingerprints, face imagery, voice, etc;

– in one site, data collection and feature extraction occur, while at another, data storage and decision-making occur. Data compression is unlikely to be required in this scenario.

– **The signal processing subsystem**. This subsystem turns the original data (or maybe the degraded data after compression and expansion) into a feature vector, attempting to retain any discriminant information that might be used to discriminate between two distinct persons while deleting redundant information.

– The purpose of feature extraction is to create a compact representation of the biometric information suitable for the pattern matching module, which compares the extracted feature vector to a number of previously stored feature vectors, one by one, yielding a numerical measure that quantifies the degree of similarity between the compared patterns.

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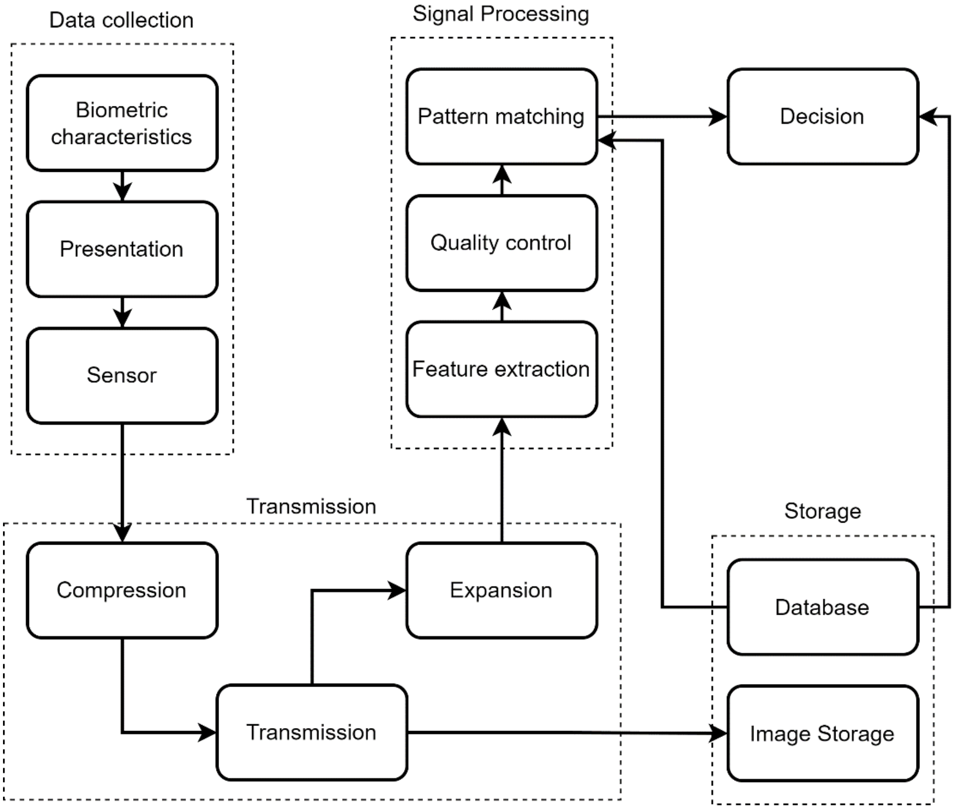

Fig. 1. **Generalized structure of biometric identification system**
Source: **compiled by the [7]**

Feature extraction and pattern matching are the foundation of all biometric technologies, and these procedures are intended to establish as much separation as possible between real and imposter distance distributions, hence reducing error rates.

The storage subsystem, which contains templates for each user registered in the system. This database may be centralized or distributed in some manner.

The decision-making subsystem. This subsystem receives as inputs the numeric values derived from the comparison of the feature vector with stored templates, and must use a technique to determine if the user is registered in the database. The decision-making procedure may be as simple as comparing the distance to a threshold (whose value is computed to meet some objective criteria).

Depending on the objective of the identification system, the actions resulting from a match or non-match may range from giving access to restricted locations or resources in the event of a match to restarting the whole procedure in the case of a non-match.

2. COMMON BIOMETRIC IDENTIFICATORS

The most common biometric identifiers are fingerprints, iris, face, and gait, among others. Consider and briefly describe several of these biometric markers.

A **fingerprint** is a pattern of ridges and furrows on the fingertip. For millennia, fingerprints have been used for personal identification, and the matching accuracy has been quite high. Patterns have been extracted by imprinting the fingertip with ink on paper. Nowadays, these patterns are captured digitally by small sensors [8].

Fingerprint recognition for identification gets the first image by a live scan of the finger via direct contact with a reader device, which may additionally check for verifying properties such as temperature and pulse.

Due to the fact that the finger actually contacts the scanning device, the surface might get greasy and foggy with continuous usage, reducing the sensitivity and dependability of optical scanners. This authentication technique is conventional and provides accuracy for contemporary fingerprint recognition systems.

Hand geometry systems provide estimations of specific hand dimensions, such as the length and breadth of the fingers. There are several ways for measuring the hand. Often, these procedures are based on mechanical or optical principles. Nowadays, the latter are far more prevalent. An individual's hand geometry is utilized for identification and recognition [9].

The qualities of a person's **voice** are determined by physical traits such as the vocal tracts, mouth, nasal cavities, and lips utilized to produce sound. Certain properties of human speech are consistent among individuals, but the behavioral component varies with age, medical problems, and emotions. In a two-factor situation, speaker verification employs speech as the authenticating element. Speaker identification aims to identify a person based on their voice.

At the third month of gestation, the **iris** starts to develop, and by the eighth month, the components that create its pattern are mostly complete. It's complicated design may include arching ligaments, furrows, ridges, crypts, rings, corona, freckles, and zigzag collarettes [9].

Iris scanning is less invasive than retinal scanning since the iris is visible from a distance of several meters. Reactions of the iris to variations in illumination may serve as a crucial supplementary indicator that the given iris belongs to a living person. Another benefit of identical twins is that their irises are not similar.

The manner in which a person writes his or her name is indicative of that person. **Signature** is a basic, physical representation of the distinct hand geometries of individuals. Sample collection for this biometric needs subject consent and a writing tool [10].

Signatures are behavioral biometrics that fluctuate over time and are affected by the subject's physical and mental state. A signature recognition system may additionally detect the pressure and velocity of the stylus over the sensor pad, in addition to the basic form of the signature.

Facial recognition is the most natural means of biometric identification. The approaches to face recognition are based on shape of facial attributes, such as eyes, eyebrows, nose, lips, chin and the relationships of these attributes [11].

As this technique involves many facial elements; these systems have difficulty in matching face images.

Table 1 shows the features of using the most common biometric identifiers.

3. GAIT RECOGNITION METHODS

An analysis of scientific literature in the field of human identification by gait reveals that gait recognition methods can be categorized into two main categories: template-based and non-template-based methods.

The objective of template-based methods is to acquire patterns of thoracic or limb movement, i.e., they typically emphasize the dynamics of movement in space or spatio-temporal methods [12]. These include the Walking Path Image (WPI) method described in [13], the Gait Information Image (GII) method [14], and the Gait Energy Image (GEI) features that can be obtained using canonical correlation analysis [15], the Joint Sparsity models [16], the Group Lasso Motion segmentation [17], and a number of others [18, 19], [20].

When it comes to human recognition, measurements that represent the shape of an object are used [21]. This is because non-template approaches take into account the shape and its features as more significant attributes.

Table 2 provides a concise summary of the deep learning-based analysis of methods for identifying a person by their gait. Researchers typically employ convolutional neural networks for gait recognition. This conclusion is predicated on the fact that convolutional neural networks can produce exceptional results in a variety of tasks and win the vast majority of machine learning competitions. However, other deep architectures also contribute to the field of gait recognition by producing superior results for certain tasks.

Table 1. **A comparative overview of the use of the most common biometric identifiers**

Biometric identifier	Identification accuracy	Ease of use	User acceptance	Ease of implementation	System cost
Fingerprint	High	Medium	Low	High	Medium
Hand geometry	Medium	High	Medium	Medium	High
Voice	Medium	High	High	High	Low
Retina	High	Low	Low	Low	Medium
Iris	Medium	Medium	Medium	Medium	High
Signature	Medium	Medium	High	Low	Medium
Face	Low	High	High	Medium	Low
Gait	Medium	Medium	High	Medium	Low

Source: **compiled by the authors**

Table 2. **Comparative review of selected scientific works in the field of gait recognition**

Year	Paper	Model	Input type	Dataset	Result	Measure
2017	[18]	CNN + Joint Bayesian	Sensors	OU-ISIR	97.6 %	Identification rate
	[29]	CNN	Optical flow	TUM-GAID	97.52 %	Accuracy
	[30]	CNN + Sia-mese networks	Cross-view	OU-ISIR	98.8 %	Accuracy
	[31]	CNN + Nearest neighbor	Optical flow	TUM-GAID, CASIA B,	99.8 %	Identification rate
	[32]	Autoencoders + PCA	GEI	CASIA B	97.58 %	Identification rate
2018	[33]	CNN+LSTM	Accelerometer and Gyroscope	whuGAIT	99.75 %	Accuracy
	[27]	GAN	PEI	OU-ISIR, CASIA B	94.7 %	Accuracy
	[34]	DBN	Sensors	own dataset	93 %	Accuracy
2019	[35]	Capsule	LBC and MMF	OU-ISIR	74.4 %	Accuracy
	[36]	CNN	GEI	CASIA B	98 %	Accuracy
	[37]	Autoencoders + LSTN	Cross-view and frontal-view	CASIA B	99.1%	Accuracy
	[38]	Autoencoders + PCA	GEI	OU-ISIR	96.15 %	Accuracy
	[39]	LSTM	Sensors	own dataset	0.02	Prediction error
	[40]	GAN	GEI	CASIA A	82 %	Recognition result
2020	[41]	LSTM	GEI	CASIA B	99.1 %	Recognition rate
	[42]	CNN	Cross-view	OU-MVLP, OU-LP	98.93%	Identification rate
	[26]	GAN	Cross-view	OU-MVLP	93.2 %	Identification rate
	[43]	Capsule	Multi-scale representations	CASIA B	84.5 %	Identification rate
	[44]	DBN	Sensors	own dataset	2.61	RMSE
2021	[45]	LSTM	IMU	whuGAIT	94.15 %	Accuracy
	[46]	Capsule	Sensors	Several	99.69 %	Accuracy

Source: **compiled by the authors**

Capsule neural networks, for instance, are capable of obtaining partial hierarchical representations of locomotion; yielding superior results when faces or objects in a scene are moving in different directions or overlapping. Recurrent neural networks, on the other hand, are of utmost importance when dealing with sequential data, such as video, and are therefore required for this method of gait recognition.

Despite the fact that the majority of deep learning approaches to gait recognition rely on images and videos of the subject area, a substantial number of studies have demonstrated success with other data sources, such as accelerometer readings, gyroscopes, sensors, and manually selected features.

The majority of this research employs unsupervised deep learning techniques, such as autoencoders and deep belief networks, which typically perform better with these types of data, whereas convolutional neural networks are the preferred option when dealing with raw image or video files.

These kinds of deep unsupervised learning approaches have the capacity to extract and change information about the distribution of data, often in low-dimensional space. This results in gait recognition characteristics that are more representative.

Finally, generative adversarial networks are utilized in certain circumstances where human gait identification systems can be trained on a wide variety of features. These features include things like orientation, clothing, number of people in a scene, and so on.

Generative adversarial networks have the ability to generate synthetic data that is used for the purpose of training models. In addition, they are helpful for analyzing the possibilities of deceiving gait recognition systems by producing false photos to test the system with. This evaluation may be done using these tools.

The Gait Energy Image (GEI) is the method that is used the most often to represent gait image data. This method presents a series of a basic energy cycle of an image by utilizing a weighted average method.

There are a number of other ways that gait image data may be represented. The sequences that make up the gait cycle are then processed such that they may be aligned to a binary silhouette [22]. As a result, GEI is able to accommodate both the static and dynamic aspects of human gait while also greatly reducing the amount of computer resources that are necessary for picture processing.

An in-depth investigation of this approach of gait representation enables one to highlight various aspects that are characteristic of this method [23], including but not limited to the following:

– a sensitivity to silhouette noise in individual photographs;

– a concentration on unique representations of human gait, which does not blur the context of vector images;

– a representation of human movement in a single image while maintaining temporal information.

In situations where gait recognition systems make use of numerous cameras to capture pictures of the environment from a variety of perspectives, one of the most common approaches to gait identification is known as the cross-view recognition technique. Input photos for such systems must come from several completely controlled cameras, and the scene itself must be controlled. In addition, these systems need to normalize the visual gait characteristics before merging the input from several cameras. This enables the model to understand the correlations between the various visual motions that are occurring in the scene [24].

The DiGGAN cross-view gait detection system, which was created at the University of Newcastle, is a good illustration of this methodology. The system produced the greatest results while utilizing the world's biggest multi-image gait dataset [25], which was accomplished via the use of the cross-validation method [26] (the dataset contains more than 10,000 people).

Notwithstanding the success that has been achieved by the gait representation approaches that have been mentioned, they have disadvantages that other gait representation methods that are not as widely used are attempting to address. For instance, the Period Energy Image (PEI) makes use of a multi-channel picture of the gait pattern. This particular approach was developed to compensate for the loss of temporal information that occurs in the GEI and cross-viewing methods [27]. A number of other publications employ an optical flow depiction of gait, which gives pertinent information about items in the scene, their spatial placement, and changes in this location [58].

Last but not least, gait identification systems that are based on deep learning also make use of a broad variety of manually chosen characteristics or sensor data. The technique of inertial measurement units is one of these approaches, as are the data from accelerometers and gyroscopes, as well as the readings from other sensors.

When it comes to the possible ways for developing contemporary gait recognition systems, we may categorize them as either being data-driven or relying on visual representations.

The 2D convolutional neural network is the most often used deep learning architecture for constructing a gait detection system utilizing data-driven scenarios (“two-dimensional” convolution networks). The 2D-CNN architecture is used by itself for classification in around fifty percent of the available solutions.

The next prominent solutions include generative adversarial networks and systems that use 3D convolutional neural networks. Around ten percent of the studied articles and research include each of these solutions (the total proportion of the analyzed publications contains twenty percent of the solutions).

Solutions that are based on deep autoencoders account for only 5 % of published papers, while recurrent neural networks account for 3 %, capsule neural networks account for 2 %, deep belief networks account for 1 %, and graph convolutional networks account for 1 %. Less common are solutions that are based on graph convolutional networks.

On the other hand, twenty-six percent of the publications provide solutions that are based on hybrid techniques. The CNN-RNN combo (which stands for convolutional neural network and recurrent neural network) is the hybrid method that is used the most often and can be found in around 15 % of studies. 10 % of the publications use the combination of DAE-GAN-RNN, which stands for deep

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autoencoder, generative adversarial network, and recurrent neural network.

Two percent of the problems may be solved using RNN-CapsNet solutions, which combine recurrent neural networks with capsule neural networks.

When it comes to the most cutting-edge systems that are based on visual representation, roughly 85 percent of them make use of a human silhouette for gait detection. While it is often described as one of the most promising approaches for visual gait identification, the use of a visual representation of the human skeleton is still only found in 10% of the publications.

This approach is commonly touted as one of the most promising methods for visual gait identification. The other 5 % of works use a variety of visual representations based on the skeleton and silhouette, using a variety of ways for synthesizing both visual representations. These works account for the majority of the total number of works.

When we think about the most significant issues and obstacles that need to be overcome in the area of human gait identification, one thing that comes to mind is the complicated nature of gait data, which results from the interaction of a number of different factors, such as occlusions and obstacles in the scene, camera viewpoints, facial appearance, the order of movement of body parts, illumination, and so on. These elements are a potential cause of problems and may impede the process of gait detection.

At this time, there is a proliferation of more sophisticated approaches in different domains connected to pattern recognition (face recognition, emotion recognition, pose estimation, etc.).

These research concentrate on gaining an understanding of perplexing settings, which enables the extraction of representations that can differentiate between various explanatory factors in a high-dimensional data space.

On the other hand, the vast majority of previously published research on deep learning gait identification has not yet investigated such methods. As a consequence of this, the currently available gait identification systems are unable to unambiguously divide the structure of the gait data into meaningful non-overlapping variables.

Even if there has been some recent success made in the form of the use of context-confused methods in some works, there is still potential for advancement in this particular field.

4. GAIT RECOGNITION DATASETS

The steps of training and evaluating machine learning models are dependent on the usage of datasets that include data from the topic area. This is true regardless of the technique that is used to train and evaluate the models (supervised, unsupervised, or any other). In addition, the use of standard data sets provides us with the ability to evaluate the efficiency of a given approach to the resolution of a certain issue and evaluate it in relation to other potential solutions.In the field of gait identification, the number of large-scale standardized datasets is small, including both public and private datasets.

This lack of training data hinders the development of new artificial intelligence models that can recognize people by the way they walk or move.

There are two obstacles to creating a large number of datasets:

– obtaining gait biometrics requires a large number of recordings of the subject's movements, meaning recording and creating several videos for each subject. In addition, such videos are usually high-dimensional, which entails the need for high-capacity data warehouses to store and manipulate the data;

– obtaining and publicly disseminating biometric data requires permission from each subject of the training data. Creating and disseminating gait datasets without the official consent of each individual may lead to lawsuits.

The next step is to analyze the gait datasets that are most commonly used for gait recognition tasks.

Table 3 provides information on the presence of covariates in a particular dataset.

Based on the results of the analysis, the covariates were divided into twelve main characteristics: viewpoint, speed, objects, shoes, clothing, time, surface, silhouette, gait oscillation, treadmill walking, ground walking, and foot pressure.

Table 4 shows the classification of datasets by the environment of dataset creation and representation (color-based and thermal information), as well as a list of works devoted to a particular dataset.

CONCLUSIONS

The research that was reviewed in this part sheds light on the primary obstacles and efforts that have been made by the research community to create strategies for approving and ensuring access to regulated resources using gait identification. The investigation also uncovered the benefits that gait-based systems provide in comparison to other types of biometric authentication methods that make use of more typical biometric characteristics. In this sense, the analysis made it possible to point out the advantages of gait biometrics in comparison to other biometric methods and to highlight the latest methodologies and state-of-the-art architectures in this field. In addition, the analysis made it possible to point out the advantages of gait biometrics in comparison to other biometric methods.

Table 3. **Comparative overview of datasets in relation to the characteristics present in the sets**

Characteristic	Dataset									
	CMU MoBo	TUM GAID	HID-UMD	CASIA	OU-ISIR	USF	SOTON	AVA MVG	KY4D	whu Gait
Viewpoint	YES		YES	YES	YES	YES	YES	YES	YES	YES
Shoe	YES	YES	YES	YES	YES	YES	YES	YES		
Time				YES	YES		YES		YES	YES
Ground walk	YES	YES	YES	YES		YES		YES	YES	YES
Surface	YES	YES	YES	YES		YES	YES		YES	YES
Clothing	YES	YES	YES	YES	YES		YES	YES		
Treadmill	YES				YES		YES			
Pace	YES			YES	YES	YES	YES			YES
Foot pressure				YES						
Ground walk	YES	YES	YES	YES		YES		YES	YES	YES
Treadmill	YES				YES		YES			
Silhouette		YES		YES	YES				YES	

Source: **compiled by the authors**

Table 4. **Comparative overview of datasets in terms of environment type and data representation**

Dataset	Papers	Environment				Representation	
		Indoor		Outdoor		Colors	Thermal
		Static	Active	Static	Active		
CMU Mobo	[21, 29, 47]	YES	YES			YES	
TUM GAID	[30, 48]	YES				YES	YES
HID-UMD	[33, 38, 49]			YES		YES	
CASIA	[24, 31, 50]	YES		YES		YES	YES
OU-ISIR	[25, 39]	YES				YES	YES
USF	[28, 42, 51]			YES	YES	YES	
SOTON	[40, 52]	YES				YES	
AVAMVG	[44, 45, 53]	YES	YES			YES	
KY4D	[32, 46, 54]	YES	YES	YES	YES	YES	YES
whuGait	[41, 55]	YES				YES	

Source: **compiled by the authors**

Regarding the gait recognition models and video-based datasets that are used in this area, there are many key factors that should be highlighted:

– when it comes to model training and testing, the datasets that were evaluated do not reflect more than one person in the video;

– the surroundings in which the datasets were recorded are entirely within the model's control. One may see that there is a lack of diversity in the items or even the backdrop colors, despite the fact that certain sets have different viewpoints;

– other videos were recorded with people walking on electric treadmills, which means even more control over the movements and the environment; as a result of this, the models that were presented in the analysis are likely to exhibit flaws and inappropriate behavior when they are applied to real-world human identification tasks (e.g., identifying the people walking on streets).

In terms of impending developments, the author of this thesis anticipates a rise in the number of scholarly articles that are connected to the following topics:

– transformer neural networks – this model is aimed at processing streaming data, such as video, which is ideally suited to the task of gait identification [56];

– gender and age recognition – gender and age recognition to improve the accuracy of human identification by gait is considered a promising area that has become increasingly popular in recent years [57];

– monitoring of hazardous environments - identification of people by gait is ideally suited to the purpose of monitoring hazardous environments, as they (environments) typically have limited illumination, making it very difficult to obtain more distinct biometric identification features [58]. This is because

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it is very difficult to obtain more distinct biometric identification features in hazardous environments;

– numerous persons in a scene - the majority of the work on gait identification focuses on the processing of video with a single person in a scene in a controlled setting. This is because several people in a scene complicate the task of identifying gait patterns. The implementation of gait recognition systems that are functional in the real world calls for the development of solutions that are resilient in uncontrolled contexts and include several individuals within the same scenario.

In addition, there is an increasing need for the ability to recognize the stride of persons when they are wearing various garments or while they are in the act of carrying goods [32]. Moreover, hybrid techniques, which include the detection of gait in addition to the use of other cues like the face or the ear, are becoming an increasingly popular choice [59].

From the author's point of view, the most promising approach is multi-view gait recognition. Multi-view gait recognition involves capturing gait data from different angles and using this data to improve recognition accuracy. Multi-view gait recognition allows of multi-sensor fusion usage. Multi-sensor fusion techniques have been used to combine data from multiple sensors, such as RGB cameras, depth sensors, and inertial sensors. This fusion of modalities can improve recognition accuracy and robustness to different environments.

The most promising datasets for multi-view gait recognition are the OU-ISIR MVLP and AVAMVG datasets because they have large population dataset with a wide view angle and presented a statistically reliable performance evaluation of multi-view gait recognition.

REFERENCES

1. Singh, J. P., Jain, S., Arora, S. “A survey of behavioral biometric gait recognition: current success and future perspectives”. *Archives of Computational Methods in Engineering*. 2021; 28 (1): 107–148, https://www.scopus.com/authid/detail.uri?authorId=57215131062. DOI: https://doi.org/10.1007/s11831-019-09375-3.

2. Wang, M. & Deng, W. “Deep face recognition: A survey”. *Neurocomputing*. 2021; 429 (1): 215–244, https://www.scopus.com/authid/detail.uri?authorId=57215104088. DOI: https://doi.org/10.1016/j.neucom.2020.10.081.

3. Hodovychenko, M. A., Antoshchuk, S. G. & Kuvaieva, V. I. “Methodology for image retrieval based on binary space partitioning and perceptual image hashing”. *Applied Aspects of Information Technology*. 2022; 5 (2): 136–146, https://www.scopus.com/authid/detail.uri?authorId=57188700773. DOI: https://doi.org/10.15276/aait.05.2022.10.

4. Bazarevsky, V. & Grishchenko, I. “Blazepose: On-device real-time body pose tracking”. *CoRR*. 2020; 1 (1): 105–110. DOI: https://doi.org/10.48550/arXiv.2006.10204.

5. Ali, S. & Karabina, K. “Formal accuracy analysis of a biometric data transformation and its application to secure template generation”. *17th International Conference on Security and Cryptography*. 2020; 1 (1): 485–496. DOI: https://doi.org/10.5220/0009888604850496.

6. Durbet, A., Grollemund, P.-M., Lafourcade, P. & Thiry-Atighehchi, K. “Near-collisions and their impact on biometric security”. *In Proceedings of the 19th International Conference on Security and Cryptography – SECRYPT*. 2022; 1 (1): 382–389. DOI: https://doi.org/10.5220/0011279200003283.

7. Wayman, J. “A generalized biometric identification system model”. *Thirty-First Asilomar Conference on Signals, Systems and Computers*. 1997; 1 (1): 291–295, https://www.scopus.com/authid/detail.uri?authorId=7003556412. DOI: https://doi.org/10.1109/ACSSC.1997.680201.

8. Alariki, A. “A review of finger-vein biometric recognition”. *Proceedings of the World Congress on Engineering and Computer Science*. 2018. 1 (1): 1–6.

9. Nandakumar, K. & Jain, A. “Biometric template protection: Bridging the performance gap between theory and practice”. *IEEE Signal Processing Magazine*. 2015; 1 (1): 88–100. https://www.scopus.com/authid/detail.uri?authorId=8950463600. DOI: https://doi.org/10.1109/MSP.2015.2427849.

10. Ross, A. & Chowdhury, A. “Deducing health cues from biometric data”. *Computer Vision and Image Understanding*. 2022; 221 (1): 1–10, https://www.scopus.com/authid/detail.uri?authorId=7402568052. DOI: https://doi.org/10.1016/j.cviu.2022.103438.

11. Petrosiuk, D. V., Arsirii, O. O., Babilunha, O. Ju. & Nikolenko, A. O. “Deep learning technology of convolutional neural networks for facial expression recognition”. *Applied Aspects of Information Technology*. 2021; 4 (2): 192–201. DOI: https://doi.org/10.15276/aait.02.2021.6.

12. Antoshchuk, S. G., Kondratyev, S. B., Shcherbakova, G. Yu. & Hodovychenko, M. A. "Depth map generation for mobile navigation systems based on objects localization in images". *Herald of Advanced Information Technology*. 2022; 5 (1): 11–18, https://www.scopus.com/authid/detail.uri?authorId=8393582500. DOI: https://doi.org/10.15276/hait.05.2022.1.

13. Zhao, X. & Zhang, H. "Gait recognition method for arbitrary straight walking paths using appearance conversion machine". *Neurocomputing*. 2016; 173 (3): 530–540, https://www.scopus.com/authid/detail.uri?authorId=56668932100. DOI: https://doi.org/10.1016/j.neucom.2015.07.012.

14. Arora, P. & Srivastava, S. "Gait based authentication using gait information image features". *Pattern Recognition Letters*. 2015; 68 (2): 336–342, https://www.scopus.com/authid/detail.uri?authorId=56702028800. DOI: https://doi.org/10.1016/j.patrec.2015.05.016.

15. Luo, J. & Tjahjadi, T. "Multi-set canonical correlation analysis for 3d abnormal gait behaviour recognition based on virtual sample generation". *IEEE Access*. 2020; 8 (1): 32485–32501, https://www.scopus.com/authid/detail.uri?authorId=56663470300. DOI: https://doi.org/10.1109/ACCESS.2020.2973898.

16. Yogarajah, P. & Prasad, G. "Enhancing gait based person identification using joint sparsity model and l1-norm minimization". *Information Sciences*. 2015; 308 (1): 3–22, https://www.scopus.com/authid/detail.uri?authorId=36844934000. DOI: https://doi.org/10.1016/j.ins.2015.01.031.

17. Rida, I. & Marcialis, G. "Human body part selection by group lasso of motion for model-free gait recognition". *IEEE Signal Processing Letters*. 2015; 23 (1): 154–158, https://www.scopus.com/authid/detail.uri?authorId=56241583700. DOI: https://doi.org/10.1109/LSP.2015.2507200.

18. Li, C. & Tang, Z. "DeepGait: A learning deep convolutional representation for view-invariant gait recognition using joint Bayesian". *Applied Sciences*. 2017; 7 (3): 1–15. DOI: https://doi.org/10.3390/app7030210.

19. Shiraga, K. & Yagi, Y. "GEINet: View-invariant gait recognition using a convolutional neural network". *International Conference on Biometrics (ICB)*. 2016; 1 (1): 1–12, https://www.scopus.com/authid/detail.uri?authorId=55337107600. DOI: https://doi.org/10.1109/ICB.2016.7550060.

20. Wu, Z. & Tan, T. "A comprehensive study on cross-view gait based human identification with deep CNNs". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2016; 39 (2): 209–226, https://www.scopus.com/authid/detail.uri?authorId=55613421800. DOI: https://doi.org/10.1109/TPAMI.2016.2545669.

21. Deng, M. "Gait recognition under different clothing conditions via deterministic learning". *IEEE/CAA Journal of Automatica Sinica*. 2018; 1 (1): 1–10, https://www.scopus.com/authid/detail.uri?authorId=56949827200. DOI: https://doi.org/10.1109/JAS.2018.7511096.

22. Luo, J. "Gait recognition using GEI and AFDEI". *International Journal of Optics*. 2015; 2015 (1): 1–6, https://www.scopus.com/authid/detail.uri?authorId=56663470300. DOI: https://doi.org/10.1155/2015/763908.

23. Han, J. "Individual recognition using gait energy image". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2005; 28 (2): 316–322. DOI: https://doi.org/10.1109/TPAMI.2006.38.

24. Ariyanto, G. "Model-based 3D gait biometrics". *International Joint Conference on Biometrics (IJCB)*. 2011; 1 (1): 105–113. DOI: https://doi.org/10.1109/IJCB.2011.6117582.

25. Takemura, N. "Multi-view large population gait dataset and its performance evaluation for cross-view gait recognition". *IPSJ Transactions on Computer Vision and Applications*. 2018; 10 (1): 12– 25, https://www.scopus.com/authid/detail.uri?authorId=23010851300. DOI: https://doi.org/10.1186/s41074-018-0039-6.

26. BingZhang, H. "Robust cross-view gait recognition with evidence: a discriminant gait GAN (DiGGAN) approach". – Available from: https://arxiv.org/abs/1811.10493. – [Accessed: March 2022].

27. He, Y. "Multi-Task GANs for view-specific feature learning in gait recognition". *IEEE Transactions on Information Forensics and Security*. 2018; 14 (1): 102–113. DOI: https://doi.org/10.1109/TIFS.2018.2844819.

28. Luo, Z. "Gait optical flow image decomposition for human recognition". *IEEE Information Technology, Networking, Electronic and Automation Control Conference*. 2016; 1 (1): 12–30. DOI: https://doi.org/10.1109/ITNEC.2016.7560427.

29. Sokolova, A. "Gait recognition based on convolutional neural networks". *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2017; 1 (1): 207– 212,

https://www.scopus.com/authid/detail.uri?authorId=57206721413. DOI: https://doi.org/10.5194/isprs-archives-XLII-2-W4-207-2017, 2017.

30. Takemura, N. "On Input/Output architectures for convolutional neural network-based cross-view gait recognition". *IEEE Transactions on Circuits and Systems for Video Technology*. 2017; 29 (9): 2708–2719, https://www.scopus.com/authid/detail.uri?authorId=23010851300. DOI: https://doi.org/10.1109/TCSVT.2017.2760835.

31. Sokolova, A. "Pose-based deep gait recognition". *IET Biometrics*. 2019; 8 (2): 134–143, https://www.scopus.com/authid/detail.uri?authorId=57206721413. DOI: https://doi.org/10.1049/iet-bmt.2018.5046.

32. Yu, S. "Invariant feature extraction for gait recognition using only one uniform model". *Neurocomputing*. 2017; 239 (1): 81–93, https://www.scopus.com/authid/detail.uri?authorId=8403845200. DOI: https://doi.org/10.1016/j.neucom.2017.02.006.

33. Zou, Q. "Deep learning-based gait recognition using smartphones in the Wild". *IEEE Transactions on Information Forensics and Security*. 2018; 15 (1): 3197–3212, https://www.scopus.com/authid/detail.uri?authorId=55628590470. DOI: https://doi.org/10.1109/TIFS.2020.2985628.

34. Fernandes, C. "Artificial neural networks classification of patients with parkinsonism based on gait". *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. 2018; 1 (1): 20–31, https://www.scopus.com/authid/detail.uri?authorId=57207456206. DOI: https://doi.org/10.1109/BIBM.2018.8621466.

35. Xu, Z. "Gait recognition based on capsule network". *Journal of Visual Communication and Image Representation*. 2019; 59 (1): 159–167, https://www.scopus.com/authid/detail.uri?authorId=57205469641. DOI: https://doi.org/10.1016/j.jvcir.2019.01.023.

36. Wang, K. "Nonstandard periodic gait energy image for gait recognition and data augmentation". *Pattern Recognition and Computer Vision*. 2019; 1 (1): 197–208. DOI: https://doi.org/10.1007/978-3-030-31723-2_17.

37. Zhang, Z. "Gait recognition via disentangled representation learning". *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 2019; 1 (1): 4705–4714, https://www.scopus.com/authid/detail.uri?authorId=57214472718. DOI: https://doi.ieeecomputersociety.org/10.1109/CVPR.2019.00484.

38. Babaee, M. "Person identification from partial gait cycle using fully convolutional neural network". *Neurocomputing*. 2019; 338 (1): 116–125, https://www.scopus.com/authid/detail.uri?authorId=56568089400. DOI: https://doi.org/10.1016/j.neucom.2019.01.091.

39. Potluri, S. "Deep learning based gait abnormality detection using wearable sensor system". *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 2019; 41 (1): 25–33, https://www.scopus.com/authid/detail.uri?authorId=52663936000. DOI: https://doi.org/10.1109/EMBC. 2019.8856454.

40. Jia, M. "Attacking gait recognition systems via silhouette guided GANs". *Proceedings of the 27th ACM International Conference on Multimedia*. 2019; 27 (1): 638–646. DOI: https://doi.org/10.1145/3343031.3351018.

41. Wang, X. "Human gait recognition based on frame-by-frame gait energy images and convolutional long short-term memory". *International Journal of Neural Systems*. 2020; 30 (1): 24–40, https://www.scopus.com/authid/detail.uri?authorId=8842192600. DOI: https://doi.org/10.1142/S0129065719500278.

42. Xu, C. "Cross-view gait recognition using pairwise spatial transformer networks". *IEEE Transactions on Circuits and Systems for Video Technology*. 2020; 31 (1): 260–274, https://www.scopus.com/authid/detail.uri?authorId=57193737516. DOI: https://doi.org/10.1109/TCSVT.2020.2975671.

43. Sepas-Moghaddam, A. "Gait recognition using multi-scale partial representation transformation with capsules". *25th International Conference on Pattern Recognition (ICPR)*. 2020; 1 (1): 25–36, https://www.scopus.com/authid/detail.uri?authorId=55027360200. DOI: https://doi.org/10.1109/ICPR48806.2021.9412517.

44. Xiong, D. "Continuous human gait tracking using sEMG signals". *Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. 2020; 42 (1): 104–116. DOI: https://doi.org/10.1109/EMBC44109.2020.9175238.

45. Tran, L. "Multi-model long short-term memory network for gait recognition using window-based data segment". *IEEE Access*. 2021; 9 (1): 23826–23839. DOI: https://doi.org/10.1109/ACCESS.2021.3056880.

46. Zhao, A. "Associated spatio-temporal capsule network for gait recognition". *IEEE Transactions on Multimedia*. 2021; 24 (1): 846–860. DOI: https://doi.org/10.1109/TMM.2021.3060280.

47. Gross, R. "The CMU motion of body (MoBo) database". – Available from: https://www.cis.upenn.edu/~jshi/humanact/publication/gross01cmu.pdf. – [Accessed: March 2022].

48. Hofmann, M. "The TUM gait from audio, image and depth (GAID) database: multimodal recognition of subjects and traits". *Journal of Visual Communication and Image Representation*. 2014; 25 (1): 195–206, https://www.scopus.com/authid/detail.uri?authorId=57200967546. DOI: https://doi.org/10.1016/j.jvcir.2013.02.006.

49. Cuntoor, N. "Combining multiple evidences for gait recognition". *International Conference on Multimedia and Expo*. 2003; 1 (1): 255–262, https://www.scopus.com/authid/detail.uri?authorId=55973123200. DOI: https://doi.org/10.1109/ICME.2003.1221261.

50. Tan, D. "Efficient night gait recognition based on template matching". *International Conference on Pattern Recognition*. 2006; 18 (1): 221–230, https://www.scopus.com/authid/detail.uri?authorId=57224746517. DOI: https://doi.org/10.1109/ICPR.2006.478.

51. Sarkar, S. "The HumanID gait challenge problem: Data sets, performance, and analysis". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2005; 27 (2): 162–177, https://www.scopus.com/authid/detail.uri?authorId=7403239642. DOI: https://doi.org/10.1109/TPAMI.2005.39.

52. Matovski, D. "The Effect of Time on the Performance of Gait Biometrics". *IEEE International Conference on Biometrics: Theory, Applications and Systems*. 2010; 4 (1): 1–12, https://www.scopus.com/authid/detail.uri?authorId=36683062500. DOI: https://doi.org/10.1109/BTAS.2010.5634547.

53. Lopez-Fernandez, D. "The AVA Multi-View Dataset for Gait Recognition". *Activity Monitoring by Multiple Distributed Sensing*. 2014; 1 (1): 26–39, https://www.scopus.com/authid/detail.uri?authorId=56429632400. DOI: https://doi.org/10.1007/978-3-319-13323-2_3.

54. Iwashita, Y. "Identification of people walking along curved trajectories". *Pattern Recognition Letters*. 2014; 48 (1): 60–69, https://www.scopus.com/authid/detail.uri?authorId=56140505300. DOI: https://doi.org/10.1016/j.patrec.2014.04.004.

55. Zou, Q. "Deep Learning-Based Gait Recognition Using Smartphones in the Wild". *IEEE Transactions on Information Forensics and Security*. 2018; 15 (1): 3197–3212, https://www.scopus.com/authid/detail.uri?authorId=55628590470. DOI: https://doi.org/10.1109/TIFS.2020.2985628.

56. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, N. A., Kaiser, L. & Polosukhin, I. "Attention Is All You Need". *NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems.* 2017; 1 (1): 6000–6010.

57. Taigman, Y. "DeepFace: Closing the gap to human-level performance in face verification". *IEEE Conference on Computer Vision and Pattern Recognition*. 2014; 1 (1): 100–112, https://www.scopus.com/authid/detail.uri?authorId=36100641900. DOI: https://doi.org/10.1109/CVPR.2014.220.

58. Santana, M. "A novel siamese-based approach for scene change detection with applications to obstructed routes in hazardous environments". *IEEE Intelligent Systems*. 2020; 35 (1): 44–53. DOI: https://doi.org/10.1109/MIS.2019.2949984.

59. Mehraj, H. "Feature vector extraction and optimization for multimodal biometrics employing face, ear and gait utilizing artificial neural networks". *International Journal of Cloud Computing*. 2020; 9 (2): 131–149, https://www.scopus.com/authid/detail.uri?authorId=57219244099. DOI: https://doi.org/10.1504/IJCC.2020.109368.

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Методи розпізнавання ходи в задачах біометричної ідентифікації людини

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АНОТАЦІЯ

Стаття присвячена визначенню проблеми вирішення завдання ідентифікації людини за допомогою розпізнавання ходи в системах біометричної ідентифікації. З метою визначення перспективності використання методів розпізнавання ходи для ідентифікації людини було розглянуто узагальнену модель системи біометричної ідентифікації, виділено основні модулі системи та надано короткий опис кожного модуля. Далі були визначені основні вимоги до біометричних ознак людини, розглянуті основні біометричні ознаки та визначені особливості їх використання в системах біометричної ідентифікації. Також було розглянуто питання використання ходи як біометричного ідентифікатора. Визначено, що використання ходи людини дозволяє позбутися двох основних перешкод при побудові систем біометричної ідентифікації: від користувачів не потрібно заздалегідь надавати персональну біометричну інформацію, а система не потребує спеціалізованого обладнання. Також було розглянуто питання розпізнавання ходи за кількома видами. Розпізнавання ходи з декількох ракурсів передбачає захоплення даних про ходу з різних кутів і використання цих даних для підвищення точності розпізнавання. Цей підхід показав велику перспективу в складних сценаріях, таких як погане освітлення. Далі ми проаналізували наукові роботи в галузі розпізнавання ходи. Було визначено, що методи розпізнавання ходи можна розділити на шаблонні та нешаблонні. Шаблонні методи спрямовані на отримання шаблонів рухів тулуба або ніг, тобто зазвичай орієнтовані на динаміку руху в просторі або на просторово-часові методи. Нешаблонні методи розглядають форму та її особливості як більш релевантні характеристики, тобто розпізнавання людини виконується за допомогою вимірювань, що відображають форму людини. Далі ми розглянемо використання різних наборів даних у процесі навчання та тестування методів розпізнавання ходи людини. Було визначено основні набори даних та зібрано їх характеристики та особливості. Розглянуто наявність різних характеристик в наборах даних, а також способи представлення інформації про ходу людини. Дослідження виявило основні проблеми та виклики, з якими стикаються дослідники в цій галузі, а також основні тенденції в галузі розпізнавання ходи людини в системах біометричної ідентифікації.

Ключові слова: Біометрична ідентифікація; нейронні мережі; розпізнавання образів; набори даних; глибинне навчання; згорткові нейронні мережі; комп'ютерний зір.

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