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A Comprehensive Review of Gait Recognition System for Human Authentication

Jaziba Anam[1], Ch. Kavitha[2], Smt. A. Sangeetha[3]

[1,2] B.E., 4/4 CSE, Chaitanya Bharathi Institute of Technology, Hyderabad, India

[3]Assistant Professor, CSE, Chaitanya Bharathi Institute of Technology, Hyderabad, India

ABSTRACT: This paper aims at reviewing gait recognition sys- tems as a novel biometric authentication modality for human identification. Gait incorporates unique features of how people walk whereby these features can be easily analyzed irrespective of background and therefore can be used to replace fingerprint or facial identification. This survey focuses on the latest development in machine learning, including GCNs and pose estimation, which can improve the performance and robustness of gait recognition systems. To enhance model performance in various realistic scenarios, we combine several datasets and apply data augmentation strategies and introduce the Unified Gait Dataset (UGD). This paper also briefly discusses the main drawbacks of the existing gait recognition methods, for example their sensitivity to environmental factors such as light or wearables including clothing and accessories and high computational complexity, which prevents their real-life usage. In addition, we discuss emerging research issues and directions that seek to address these limitations hence serve to further the gait based security and healthcare applications. The conclusions consider the possibility of developing gait recognition systems using machine learning and applying new sets of data inputs for increasing the security and reliability of such systems.

KEYWORDS: Gait Recognition, Machine Learning, Graph Convolutional Network, Human Authentication, Pose Estimation

I. INTRODUCTION

Over the last decade, technologies used for human identification have been of great importance in several areas such as security purposes in surveillance and healthcare. Biometric approaches that are normally used include fingerprints and face recognition, and they have shortcomings in that they can be forged, and environmental conditions affect them. Gait recognition provides a better solution to this problem because it is based on the gait of individuals, which is invariant to environmental conditions. This makes gait recognition a more reliable method of identifying human beings since people often move in dynamic and diverse ways. Nonetheless, current gait recognition systems have the following limitations, primarily due to environmental conditions, clothing, and carried objects. These factors can cause unpredictable system performance, greatly diminishing the usefulness of the technology in fields like security and healthcare. Current models also consume considerable time during testing and are highly error-prone as they depend heavily on physical and environmental variations, making them less ideal for real-life scenarios.

To overcome these problems, this work proposes to design a novel gait recognition system based on machine learning to improve performance under diverse environments. By creating the Unified Gait Dataset (UGD) through the combination of multiple datasets and applying data augmentation, the model will be trained under varied conditions, enhancing general- ization capabilities. The inclusion of Graph Convolutional Networks (GCNs) will further capture spatial features of gait patterns, thereby improving model robustness across different conditions. The aim is to improve gait recognition technology with enhanced practical usability.

II. RELATED WORK

A. Overview of Gait Recognition Methods

Gait recognition means recognition of the gait of an individual, and gait analysis have been found to be very accurate for the biometrics human recognition system. Traditional methods employ outline-based schemes, Fourier transforms along with classifiers including SVM and HMM, given feature vectors from the video or the motion capture data. It has some limitations on how efficiently it can address changes in the environment; for instance change in level of lighting or background music. But, from the improved strategies, such as CNNs and RNNs, the accuracy has improved since the model learns hierarchy features of the order and temporal dependency of gait sequences.

Four new trends of MM gait recognition are different from the previous trends as: It fills the need and tends to be immune to conditions of the traditional gait recognition using different techniques such as depth cameras, thermal imaging, and wearable devices. Surprisingly, CNNs and LSTMs turn out to be very effective but some of the disabilities include; environment sensitivity, conditions in the data sets used, and security concerns. The future work is to remove these limitations, improve the generalization of the gait recognition method, and address different ethical issues for using the gait-based biometrics in practice for security and surveillance systems, health care and access control applications.

B. Key Findings from Literature

[1] The development in the gait recognition is presented in this paper where deep learning approach including CNNs, RNNs, GANs and attention mechanism improves on its accuracy and performance at different angles. The applications of this type of research ranges from surveillance based identification to healthcare in mobility assessment. Nevertheless, current models are mainly adjective based and there is a lack of research that focus on model based methods. Therefore, according to the findings in this paper, utilizing a mixture of both methods is recommended as a way of enhancing recognition accuracy into human faces; as well as its resistance to various attacks. The elements of the deep-learning model-based approach in combination with model-based strategies leads to the enhanced potential to synthesize accurate and adaptive gait recognition across various applications.

[2] An analysis of gait recognition approaches that establish 3D body shapes from silhouettes sequences, keeping constant effects of view point, clothing, carried object. This method also improves identification precision in complex situations, mainly due to the concentration on structural characteristics, not physical attributes. However, the use of silhouette based datasets and limited availability of RGB images restricts the usage of this model in non-RGB datasets and may not be resilient in real-world applications. Regarding these challenges, the paper proposes more directions for methods incorporating multiple data types with the expected increase in scale and robustness under different environments.

[3] Notably, this paper presents the BRIAR dataset that can enhance the person recognition by offering the best quality biometric data obtained through large distances and high altitudes which can sensitive the gap left by other datasets in UAV surveillance. The dataset contributes to the enhancement of model performance in typical scenarios of real-world surveillance. Nonetheless, there are limitations to the generalization of using such data in the training of biometric models due to a skewed demographic distribution by age and race. The following recommendations are made in this paper to increase the inclusiveness of the above dataset and increase the stability and fairness of person recognition systems in different populations.

[4] This paper presents gait-based authentication system using Decision Tree Classifier having a very high accuracy of 95logistic regression, and Na¨ıve Bayes. This shows high viability of gait based authentication using decision trees from an experimental perspective as performed by the two algorithms. Nevertheless, the comparative analysis of the study is somewhat limited by the comparison only with some of the traditional ML models, and this study likewise does not include any of the deep learning approaches for gait recognition. For future work, the authors suggest the comparison of the proposed methods with deep learning methods and also more experiments comparison for the evaluation of the models’ stability and possibilities in real authentication conditions.

[5] We also present the DME approach for the whole body recognition that uses the RGB and silhouette data to improve the results in various poses and environments. Accompanying the DSME approach is the ability to apply it to different type of databases: CASIA-B internal and BRIAR outdoors; the DME approach is thus more effective than the majority of modern templates. However, GaitPattern module using Double Helical Signature is designed mainly for indoor navigation and as far as key-point detection is needed for identification, this system’s robustness is not very high in unconstrained outdoors area. As for these limitations, the improvements in the key-point detection models could be the primary direction of the further study in order to extend the applicability of the developed approaches to the dynamic settings in real-life conditions.

[6] In this paper, a new taxonomy for deep gait recognition is proposed and the methods are classified by body structure, temporal, feature, and neural. Through the various components of this structured approach, the state of the art and future of vision-based gait recognition based on deep learning models are set out coherently. That being said, the taxonomy mainly aims at the deep learning, while the methods based on non deep learning, as well as the sensing modalities, such as wearable sensors, are beyond its scope. To encourage to work on gait recognition for a better view, in future general framework of gait recognition should include a wider range of techniques apart from vision-based, and should comprise methods from other modality for their flexibility and ability to be applied for a wider range of purposes.

[7] To this end, this paper presents GaitNet – a deep learning architecture that jointly disentangles appearance, canonical shape, and pose features from the RGB videos for improved gait recognition. GaitNet achieves superior results than other current techniques using the CASIA-B, USF, and FVG databases that prove its applicability with different data sets. However, GaitNet is not resistant to extremely low resolution environment and is affected by significant illumination changes as evident in the documented failures. The subsequent works are likely to investigate the resilience of GaitNet to shifts in the image resolution and lighting conditions to achieve practical purposes with the presence of diverse environment perturbations.

[8] Available from Gait Recognition and Its Applications in Biometrics – A Survey. This paper analyses

various gait recognition techniques and their applications in biometric systems. Model-based and appearance-based solutions are briefly introduced, explaining how both approaches can be employed to accomplish model gait recognition. Environmental changes, including lighting, angle assumptions, and clothing, are considered as limitations in the paper. It also provides a brief description of datasets used in gait recognition. Furthermore, the paper discusses the focused implementation of gait recognition in mobile and surveillance environments, where frequent tracking of people in public spaces is conceivable.

[9] Gait Recognition Using Deep Learning: This paper demonstrates how deep learning patterns can be applied to gait identification. Various types of deep learning techniques, including CNNs, LSTMs, and autoencoders, are presented, examining their suitability in various gait recognition scenarios. The paper evaluates how these methods are superior to simpler gait recognition techniques. It also studies emerging issues that deep learning models can address in real-world scenarios, such as changes in walking manners and conditions involving carrying objects, among others.

[10] Gait Recognition Using Kinect: This work explores the possibility of using the Microsoft Kinect sensor for gait-based recognition. It particularly addresses how Kinect's depth-sensing feature can be employed to obtain skeletal features of walking individuals. The paper assesses the accuracy of Kinect-based systems in recognizing individuals based on their walking patterns and includes a comparative analysis of Kinect-based systems with other vision-based systems.

[11] A Novel Gait Recognition System Using Multimodal Fusion [11] This research presents a new system of gait recognition based on video data, depth data, and inertial sensor data. The approach demonstrates that the multimodal fusion can improve the accuracy of recognition since each input provides complementary information. Experimental results show how fusion improves gait recognition in occlusion and environmental noise.

[12] Deep Learning for Gait Biometrics This review paper provides profound insights into the way deep learning technologies have been used for gait biometrics. This paper describes various deep learning architectures for gait recognition, such as CNNs and RNNs, and outlines the importance of gait recognition in security and surveillance. It also analyzes the potential issues which may affect gait recognition in real-world application, such as a huge volume of dataset, occlusion and model bias, and discusses the solution to this issue..

[13] The Identification of the human gait has been investigated using diverse sensors including accelerometers and depth sensors especially the 'Kinect'. Previous approaches involve the use of both static and dynamic gait characteristics in order to enhance the possibility of recognizing the gait and the time normalization to reduce the difference between the lengths of the walking cycle. k-NN and LSTM classifiers for gait patterns have been applied before, although the LSTM architectures are preferable for sequential gait information. This research extends these approaches to improving the identification accuracy using features of gait and classifiers.

[14] Biometrics identification and identification studies as fundamental topics of today's world are making use of the differences that every human has, including ear, odor, heartbeat, voice, iris, face, fingerprint, gait and so on. Among these, gait recognition deserves more attention as a technology capable of recognizing a subject without his/her cooperation, even when using low-quality images. The system developed in this paper to identify the person employs the techniques of Deep Convolutional Neural Networks (DCNN) for gait feature extraction where Gait Energy Images (GEI) are employed. To optimize the gait features for accurate recognition, system mentioned trains the DCNN architecture to better come up with normalization of gait features.

[15] Therefore, the human gait recognition method in frontal-view gait motion using gait dynamics and deep learning will be presented in this paper. Contrary to conventional lateral-view methods, it samples gait characteristics including kinematic, spatial rate/ ratio and area characters from binary walking silhouettes. It also integrates real-time gait motion data and develops a deep feature extraction mechanism to achieve higher accuracy and resistance. Recognition perfor- mance is improved under different walking conditions using an error based feature fusion technique.

III. INSIGHTS FROM LITERATURE AND EXISTING CHALLENGES

Current gait recognition systems face several challenges that limit their applicability in real-world scenarios. These challenges are categorized as follows:

A. Environmental Variability

[3], [5], [7], [8], [11], [12] Some systems for gait recognition are handicapped by the problem of poor recognition even when conditions vary, including different lighting, weather or terrain conditions. It is much more difficult to maintain the signal purity and to carry out measurements because the surrounding environment adds distortion that greatly lowers system performance for dynamic and/or outside applications. This issue is well elaborated when the recognition system is in conditions like UAV surveillance, poor illumination or blurred images and Accessories

B. Clothing and Accessories

[2], [8], [9], [15] This is due to that in addition to the various ways people may change their garments or wear accessories, over garments such as bags, coats or even bags, back packs etc. may greatly affect human walking mannerisms. These variations form a big problem especially when trying to extract consistent gait features hence the low accuracy. Such

changes are detrimental to the methods which are based much on shape and motion such as silhouette-based methods since a person may wear different cloth or carry an object unlike in the above example.

C. Carried Objects

[2], [8], [9], [15] Implements shifted with things like laptops, shopping bags or other objects change the walking pattern and lead to misidentification in most if not all current systems. This is a serious issue because the items that a person holds often modify or actually occlude the shape of the person’s affect, which poses difficulties for silhouette-based Figures as well as model-based recognition systems..

D. Computational Overhead

[1] , [6], [7], [9], [12], [15] Models especially deep learning based models are resource demanding meaning that they would need enhanced processing power and memory to run as expected. This makes real time application complex par- ticularly for constrained systems like the edges, or systems in the mobile platform. Though models like the CNNs and RNNs are very accurate, they have high time and memory complexity and cannot be adopted for real world application where efficiency is important..

E. Dataset Limitations

[2] , [3], [5], [7], [8], [12], [15] One of the most significant weaknesses of lim recognition systems is that they are based on restricted and rather biased samples of data. These datasets do not encompass all the possible variations of real-world walking such as age difference, color, and ways of walking. In this light, models developed using such datasets, often exhibit subpar performance whenever implemented in other settings or on dissimilar people. The commonly used databases are CASIA-B, USF, and FVG; however, they lack the ability to cover all possible real-world gait dynamism.

Findings Based Analytical Comparison:

1) Traditional ML Methods: One of the first methods in gait recognition is Support Vector Machines (SVM), Hidden Markov Models (HMM), etc. These methods use such handcrafted approaches for classification as Fourier Transforms and motion data for classification. They use less computation and are also less complicated making them ideal for controlled circumstance. However, their information-processing capabilities depend on the envi- ronment (for example, lighting or background) and are problematic in modern large cases and tasks requiring

Table I Expanded Comparative Study Of Gait Recognition Methodologies.

Methodology	Key Techniques	Strengths	Limitations
Traditional ML	SVM, HMM, Fourier Transform	Simple, computationally efficient	Sensitive to environmental variability, limited scalability
Deep Learning	CNNs, RNNs, Autoencoders, GaitNet	High accuracy, learns complex temporal and spatial features	High computational cost, limited by dataset diversity
Silhouette-Based	Silhouette extraction from video frames	Effective in controlled settings, computationally efficient	Sensitive to clothing, carried objects, and occlusions
Appearance-Based	Gait Energy Image (GEI), spatial texture analysis	Incorporates detailed appearance features	Affected by lighting and background variability
3D Model-Based	Depth cameras, skeleton tracking	Captures structural features, viewpoint invariance	High computational cost, requires specific sensors
Multimodal & Sensor-Based	RGB + Depth data, Thermal imaging, Wearable sensors	Robust against environmental changes, complementary data	Expensive, sensor-specific challenges
Pose Estimation	OpenPose, keypoint tracking	Extracts dynamic gait features, effective for motion analysis	Sensitive to occlusion, computationally demanding
Frontal-View Gait Recognition	Gait dynamics from frontal-view sequences	Effective in constrained scenarios, integrates kinematic and spatial features	Limited applicability in lateral or dynamic views
Real-Time Systems	Optimized CNNs, lightweight models	Applicable for edge and mobile platforms	Sacrifices some accuracy for speed
Dataset-Specific	CASIA-B, FVG, BRIAR	Effective on known datasets	Lack of generalization to unseen environments

Table II: Comparison of Various Metrics

Method Type	Accuracy (%)	Error Rate (%)	Training Time (hrs)	Computational Cost (FLOPs)	Robustness to Occlusions (1-10)	Sensitivity to Environmental Factors (1-10)
Traditional Machine Learning	75-85	15-25	2-5	Low	5	6
Silhouette Based	70-80	20-30	1-3	Medium	6	5
Deep Learning Approaches	85-95	5-15	5-10	High	8	7

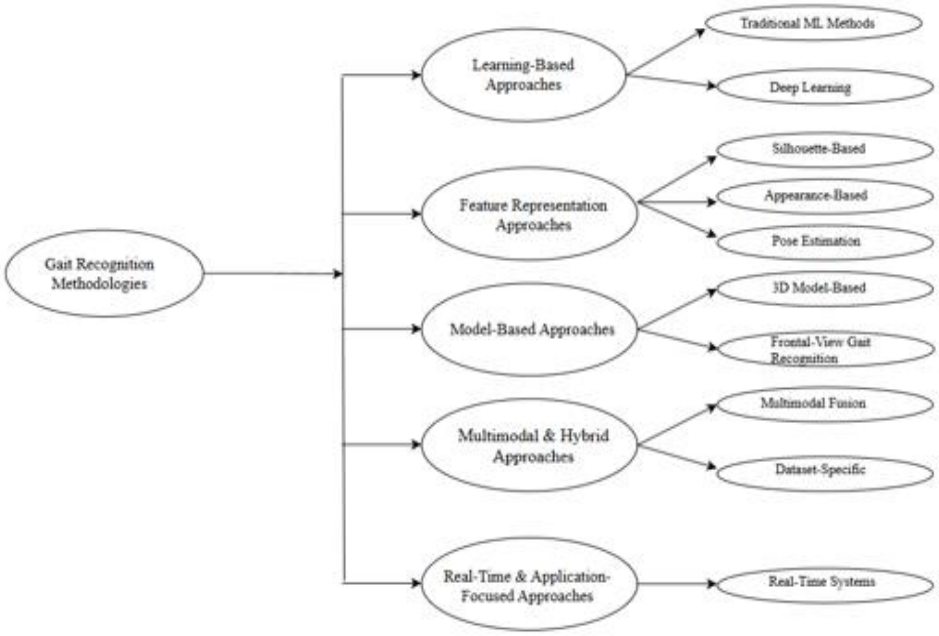

Fig. 1. Comparative Study of Gait Recognition Methodologies

Additional spatial scales.

2) Deep Learning: Advanced techniques in gait recognition include CNNs, RNN and the mixed model of Deep GaitNet. These models inherently discover nonlinear spatial and temporal relationships from data and provide good accuracy for various datasets. Nevertheless, deep learning methods are compute intensive and generally challenged by diversity of datasets, which hinders their applicability in real world settings.

3) Silhouette-Based: Methods based upon silhouettes record and analyze the outer contour of a person's body in subsequent frames of a video. These are computa- tionally effective methods and are effective in indoor environments only. Such representations work well when there is consistency in the clothing, objects that the person may be holding and occlusions, which may all distort the extracted features diluting the recognition factor.

4) Appearance-Based: Compared to previously discussed methods, appearance-based methods make use of more detailed visual features like Gait Energy Images(GEI), or spatial texture analysis for instance. These techniques collect more detailed information that makes it suitable in cases of recognition. However, they are extremely sensitive to illumination, scene and view point shifts

which in turn affects their performance in real scenes.

5) 3D Model-Based: Such methods base their operation on depth cameras and skeleton tracking to build three-dimensional models of an individual's gait. This way, by capturing the structural features they guarantee ro- bust ness with respect to viewpoint and environmental changes. Its main disadvantages include high computa- tional needs, and the reliance on specific sensors, which hinders their application.

6) Multimodal Fusion: Multimodal learning scenarios in- corporated several data types including RGB, depth, thermal vision and wearable cameras. This fusion pro- vides both strong adaptability to environmental perturba- tion and camouflage and closer to real-world problems. However, these methods are expensive and problems occur due to individual sensor specifications.

7) Pose Estimation: Pose estimation techniques, such as OpenPose, track key points of the body to analyze dynamic gait features. These methods excel in capturing motion and are particularly effective for identifying individuals based on their unique walking patterns. Nonetheless, they are computationally demanding and sensitive to occlusion, which can impact accuracy in crowded scenes.

8) Frontal-view gait recognition Unlike the traditional lateral-view based methods, frontal view-based gait recognition focuses on an analysis of dynamics from a front view. These methods are viable in constrained applications where lateral views are not present and include some kinematic along with spatial features but are applicable under specific contexts alone and do not generalize well into lateral or dynamic view-based applications.

9) Real-Time Systems: Real-time gait recognition uses optimized deep learning models for the speed and ef- ficiency needed. It can be deployed on edge devices and mobile platforms. For such applications, surveillance and access control, such systems are very practical but at a loss of some accuracy for real-time processing requirements.

10) Dataset-Specific: These methods are tuned to particular datasets, like CASIA-B, FVG, or BRIAR, and optimized to perform under the conditions represented in the data. Such methods are useful for benchmark comparisons but do not generalize to unseen environments or datasets, which speaks to the requirement of more diverse and comprehensive training data.

IV. DATASET

This unified gait dataset is developed in the process of combining multiple sources of covering limitations that single gait datasets have; innovative augmentation techniques, and the management of demographic diversity. These complete datasets are attempting to provide robustness and inclusiveness for gait recognition systems.

Data Sources

The UGD integrates data from the following leading datasets:

1) CASIA-B: Selected based on its wide sequences that have been taken with various observation angles, hence presenting varied gait and occlusion scenarios.

2) USF HumanID: Has gait data acquired in varied en- vironmental conditions, so useful for generalization to outdoor environments. (Front-View Gait): Has data mainly acquired from frontal views, which serves as a complement to the CASIA-B heavily-lateral-viewed and adds variety to the database..

These datasets have been selected based on complemen- tary characteristics like diverse perspectives, environmental aspects, and demographic diversity. This in turn also leads to a more comprehensive gait variability in realistic situations.

Augmentation Techniques:

- Data augmentation is the backbone of the UGD with a view to enhancing the generalized ability and robustness of the model. The techniques utilized are as follows:
- Adding Noise: This simulates the imperfections in sen- sors to ensure that the model is robust to noisy inputs.
- Illumination Variations: It adjusts brightness and contrast to simulate different lighting conditions, one of the major limitations of gait recognition.
- Geometric Transformations: It involves rotation, scaling, and flipping to augment spatial diversity.
- Pose Variation Simulation: This introduces synthetic vari- ations in gait poses to simulate real-world conditions like carrying objects or changing walking styles.
- Such enhancement techniques enhance the ability of this dataset to better reflect the real-world nature of events and enhance generalizability of any learned model.

Diversity and Inclusivity: In terms of demographic biases, The UGD deals with the following:

- Demographic Balance: Sources for the data have been selected so that the age, gender, and race are evenly distributed. This is done to ensure the model does not learn bias in the data against particular groups.
- Variation in Walk: The dataset has data in walking with speed, gait styles, and extraneous variations, such as carrying bags, different clothing types, etc.
- Diversity in Environment: It comprises of indoor, outdoor, and mixed environments for broad real-world variability.

UGD aims to provide a dataset that reflects the diversity and complexity of human gait in real-world applications by incorporating these dimensions.

Evaluation Protocol

To ensure rigorous benchmarking, a standardized evaluation protocol is adopted by UGD.

Dataset Splitting:

- Training Subset: Use 70% of the data to train the machine learning algorithm.
- Validation Subset: 15% of the data to avoid overfitting due to hyperparameter tuning.
- Testing Subset: Utilize 15% to get the final performance.

Performance Metrics:

- Accuracy: Percentage accuracy of correct identification of gaits.
- Precision and Recall: Measures the model’s reliability and ability to handle imbalanced data.
- Robustness Metrics: Evaluation under occlusions, noise, and varying environmental conditions.
- Cross-Dataset Validation: Models trained on UGD will be validated against unseen datasets to assess generalization capabilities.
- Benchmark Comparisons: Comparisons with existing benchmarks to highlight the improvements brought by UGD.

By following this protocol, UGD ensures that the trained models are rigorously tested for real-world applicability and robustness.

V. CONCLUSION

Accordingly, gait recognition systems using methods like GCNs, pose estimation along with machine learning are good candidates for designing future human authentication systems. However, there are still a number of difficulties which have not undergone considerable improvements and which pose certain obstacles to applying current models in practical endeavours. Certain bottlenecks including environmental fluctuations in illumination condition, the subject’s wear of different clothes and accessories, objects the subject carries, increased complexity in computations, and restricted variation of datasets must be given adequate attention for the enhanced reliability and efficiency of gait recognition.

Then to manage these challenges in the future, researchers should strive to increase the generalization capability of these systems by using more data by practices like data augmentation and fusion. The use of more advanced models, for example GCNs, and incorporating multimodal data can be expected to yield steps in bettering the variations of walking patterns and environmental changes. Furthermore, these reductions are important for this kind of system to be practically feasible in real-time situations for mobile or edge computing platforms.

Basically, it is concluded that even if the gait recognition has a promising prospect, further studies synergistically related to deep learning, wider dataset database, and improvement of gait recognition system will be required to develop the gait recognition widely as the ideal biometric authentication system across various areas of security, healthcare, etc..

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