Review of gait recognition systems: approaches and challenges

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ABSTRACT

Gait recognition (GR) has emerged as a significant biometric identification technique, leveraging an individual's walking pattern for various applications such as surveillance, forensic analysis, and person identification. Despite its non-intrusive nature, GR systems face challenges due to their sensitivity to pose variations, limiting functionality in real-world scenarios where people exhibit diverse walking styles and body orientations. This review paper aims to comprehensively discuss GR systems, focusing on approaches and challenges in designing accurate and robust systems capable of handling bodily variations. GR's prominence spans across domains including surveillance, security, healthcare, and human-computer interaction, positioning it as a versatile biometric modality complementary to the traditional methods like fingerprint and face recognition. The review offers an in-depth analysis of GR systems, detailing silhouette-based, model-based, and deep-learning approaches. Silhouette-based methods capture gait information by analyzing the outline and locomotion of a person's silhouette, while model-based approaches utilize skeletal models to describe gait patterns. The paper elucidates the challenges and limitations of GR systems, encompassing factors such as walking conditions, clothing, viewpoint, and environmental influences. Additionally, it explores potential future directions in GR research, highlighting the technology's ongoing evolution and integration into diverse applications. As a valuable resource, this review serves researchers, practitioners, and policymakers by providing insights into the current state of GR systems and avenues for further research and development. It underscores the importance of addressing challenges to enhance GR's accuracy and robustness, ensuring its continued relevance in biometric identification across various domains.

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1. INTRODUCTION

Gait recognition (GR) is a biometric identification technique that involves analyzing an individual's walking pattern or gait for identification or authentication. It is based on the principle that each individual has a distinctive way of walking, influenced by factors such as body structure, weight distribution, and muscle movement patterns. GR has garnered interest as a potential biometric identification technique due to its non-intrusive nature and the ability to provide continuous monitoring in real-world scenarios. It uses computer vision techniques to extract and analyze features like step length, step rhythm, and the body movements from video footage of a person walking.

Here are some key aspects and contexts related to GR as a biometric identification technique: i) Biometric identification: GR is a form of biometric identification, which means it relies on distinctive and measurable physical or behavioral characteristics of individuals. Other examples of biometrics include fingerprints, facial features, iris patterns, and voice recognition, ii) non-intrusive and passive: GR offers a non-intrusive and passive way of identifying individuals without requiring their cooperation or active participation. Unlike other biometric techniques that may require physical contact or explicit actions, GR can be performed from a distance using video footage or sensor data, iii) unique gait patterns: Research has shown that people have novel gait patterns that are suitable for identification. Factors such as leg length, body proportions, joint flexibility, and walking style contribute to the distinctiveness of an individual's gait. GR algorithms analyze these patterns and extract features for identification purposes, and iv) applications: GR holds promise for numerous applications across diverse fields. Among the notable applications are surveillance and security systems, access control in high-security areas, forensic investigations, monitoring and identifying individuals in crowded spaces (*e.g.*, airports, stadiums), and healthcare for remote monitoring or detecting abnormal gait patterns.

2. BACKGROUND

For a very long time, researchers have actively studied human gait in the fields of physical medicine (gait problems resulting from stroke or cerebral palsy) [1], athletics (gait regulation) [2], and sociology (age and gender classification) [3]. Murray's early psychology research [4] revealed that gait was a distinct individual trait that had rhythm and was inherently cyclical. Overall, the study provides insight into the unique challenges that visually impaired athletes face and how they adapt their gait to overcome these challenges during the Phase of the long jump approach. As data mechanism reliability progresses, experimenters are looking into and aim to employ gait as a biometric indicator to identify known individuals [5], [6]. Within the domain of computer vision, it has gained increasing attention, and several gait metrics have been created. This research proposal uses the term "GR" to denote the recognition of a person from a video clip in which the person is shown walking as shown in Figure 1. The stride of regular walking, clothes, and carrying condition variations are displayed in three samples, arranged from left first, moving towards right. This does not imply that gait is only relevant to walking; it applies to running and other foot-based activities as well [7].

Figure 1. Contrast-enhanced photos in the CASIA gait database's gait sequences (dataset B) [8]

3. LITERATURE REVIEW

Research in human GR has experienced a boom over the past 15 years. As far back as the 90's, scientists were working with systems that had a > 90% recognition rate. Yet, despite having a tiny database, the research attracted considerable attention. Current research is indeed more sophisticated and the methods developed are more sensitive. Comparing the old methods with new ones acts not only as an indicator of meaningful research but also because of the natural interest of some researchers. Even with GR's remarkable success with deep learning approaches, there are still a lot of issues in the field that need to be resolved. Here, the survey that follows identifies some more interesting areas for further study as well as unresolved issues in this field. These paths will make it easier to conduct further research in this area.

Elharrouss *et al.* [9] suggested a GR method for re-identifying individuals. This method begins with measuring the gait's angle and then uses convolutional neural networks (CNNs) to perform the task of identification. To calculate the angle and identify the gait, the multitask CNN models along with extracted gait energy images (GEI) are utilized. A set residual network for GR is proposed by Hou *et al.* [10] in an effort to extract additional discriminative characteristics from the silhouettes. To extract the set-level and silhouette-level features simultaneously, they suggest using a set residual block. Enhancing silhouette-set interaction is necessary to efficiently extract features from the silhouettes, and coordinate both set-level and silhouette-level data. To do this, a residual connection is used to connect the two-level features within each block. Semwal *et al.* [11] investigated three new object identification techniques: Zernike moment for cross-view invariance using random transform, gradient histogram for multi-view invariance, and gait energy image for fabric invariance. Artificial neural networks (ANN), and support vector machines (SVM), along with lately developed methods, such as machine learning approaches based on XGBoost, are employed to classify data.

In order to expand on current datasets related to gait and offer ample gait samples for deep learning-oriented cross-view GR techniques, Chen *et al.* [12] use a multi-view gait generative adversarial network. In addition to performing domain alignment determined by the predicted peak mean discrepancy to lessen the impact of divergence in distribution induced by sample production, this approach trains one generator to handle all view pairings included in one or more datasets. Wang *et al.* [13] created a new feature of gait depictions called trituple gait silhouettes, which is made up of sequential gait silhouette photos, as an alternative to the gait energy photographs used in classic GR. After that, a several-channel CNN network is built to process a series of sequential images simultaneously.

For the first time, a method of GR based on a single image is proposed by Xu *et al.* [14], enabling latency-free GR. Using an auto-encoder framework, they first regenerate entire successive sequences of gait cycles depicted in images using the single images, which reduces significant differences in phase (gait position) between a matched pair of input single images that result in intra-subject variances. These full gait cycles are then fed into a cutting-edge GR network for matching.

Complex gait data is the result of multiple factors interacting, including obstruction, viewpoints of the camera, individual appearance, order of sequence, body component motion, and sources of illumination in the data [15]–[17]. The recognition task may become more challenging due to the intricate interactions between these components. Unique generative models and loss functions can be adapted to acquire greater selective gait depictions by clearly separating the components of identity and non-identity, which could lead to future advancements in this field. Multi-task learning aims to use a common model for learning numerous tasks at once, leading to the acquisition of more broad and often reinforced representations. These methods frequently provide benefits including faster convergence, better learning by utilizing auxiliary data, and decreased overfitting by using shared representations. Because of this, the majority of current studies learn identity-sensitive features without considering how they interact with other latent factors like age, gender, and affective states [18]–[20]. Given this, learning several tasks for GR simultaneously could lead to novel design approaches and optimization problems, particularly with regard to task identification and loss functions.

The somewhat altered circumstances might cause a significant change in look, which could prevent recognition. Gait can be impacted by physical changes (pregnancy, injuries, and weight gain/loss), clothing (length cloak, shoes, and carrying goods), and contextual context (walking surface and background). Even though each person's gait is different, a number of variables are at play. Gait will alter with time due to many factors such as injuries [21], pregnancies [22], natural aging [23], changing weight [24], and so forth. It is interesting to note that Perera *et al.* [25] claimed in 2016 that gait velocity can predict mortality and impairment spanning a three-year period because gait is such an expressive phenomenon. The way someone walks might be altered by mood swings and transient stimulants like alcohol and drugs. Intentionally or inadvertently, a person's wide gait variance under various circumstances decreases the biometrics' ability to discriminate. Another difficulty is accurately separating the foreground walking subject from the background scene, and there are sometimes variations in the camera viewing angle in relation to the walking subjects. More gallery samples taken from various environmental contexts are needed to capture large variances of the same individual under different conditions.

Bukhari *et al.* [26] introduced a CNN-based approach for managing known covariate conditions solely through the utilization of simple GEI. Additionally, they employed a discriminative feature learning method to address unknown covariate conditions. The images undergo size normalization and horizontal alignment processing. Subsequently, the gait cycle segmentation is estimated using techniques such as gait frequency estimation and maximum entropy estimation. The calculations of the GEI are then conducted, employing in (1),

$$GEI = G(x,y) = \frac{1}{T}\sum_{t=1}^{\mathrm{T}} \mathrm{I}(\mathrm{x},\mathrm{y},\mathrm{t}) \tag{1}$$

In (1), T represents the entire quantity of frames per gait cycle, while x and y denote the pixel coordinates of the silhouette image I, and t signifies the frame number within a gait cycle. Lin *et al.* [27] consider the gait sequence's silhouettes as a video. Global-local based gait recognition network (GaitGL) customizes 3D convolution to ensemble global and local features. Huang *et al.* [28] proposed gait recognition frameworks employing CNNs to generate distinctive feature representations. It integrates the decoupling of spatial-temporal correlation into a 3D convolution framework. Zhang *et al.* [29] proposed gait-related loss function, called angle center loss (ACL), to learn discriminative gait features. These approaches retain a greater amount of temporal information. However, they may experience notable deterioration if an input comprises discontinuous frames or possesses a frame rate distinct from that of the training dataset. Human gait recognition derived from frontal-view sequences using gait dynamics was studied by Deng *et al.* [30]. The approach uses frontal-view gait parameters, such as the kinematics, spatial ratio, and area features, to describe the binary walking silhouettes.

In addition, some researchers have proposed using 3D GR methods to develop pose-invariant GR systems [31]. The 3D GR system can capture the three-dimensional information of the gait, which is unaffected by the pose and the walking speed of the person. This method has shown favorable outcomes in various applications, such as the Kinect sensor-based GR system [32].

4. PUBLIC GAIT DATASETS

GR research often relies on various datasets to develop and evaluate GR algorithms. Here are some popular gait datasets that researchers commonly use:

a. CASIA gait datasets (CASIA): CASIA dataset is among the most popular datasets for GR. It includes multiple subsets with different variations, such as view angles, clothing, carrying bags, and walking directions. CASIA A dataset is a popular choice for benchmarking GR systems [8].
b. OU-ISIR gait database (OU-ISIR): Created by Osaka University and The Institute of Intelligent Systems and Robotics (ISIR), this dataset contains a substantial number of subjects. It includes both RGB and depth data, making it suitable for different GR approaches [33].
c. Surrey University gait dataset (SURREY): This dataset contains various walking scenarios, including outdoor environments. It provides RGB and depth data along with annotations for each frame [34].
d. TUM gait from audio and image sequences (TUM GAIS): TUM GAIS includes audio and image sequences recorded in uncontrolled environments. This dataset is valuable for research that focuses on realistic scenarios [35].
e. GAIT-ITI dataset (GAIT-ITI): Collected by the International Tomographic Imaging (ITI) research group, this dataset offers RGB and depth videos for GR research. It includes both indoor and outdoor scenes [36].
f. Georgia tech VR gait database (GTVG): This dataset includes gait sequences of individuals walking in a virtual reality environment. It is designed to study GR in immersive and controlled conditions [37].
g. Walking gait datasets by Ohio State University (OSU): Ohio State University has contributed various gait datasets, including sequences with different clothing and carrying conditions. These datasets are suitable for researchers interested in studying the impact of these variables on GR [38].
h. Oulu-NPU gait database (Oulu-NPU): This dataset features walking sequences captured using depth sensors. It includes subjects from various age groups and walking speeds [39].
i. Columbia University gait dataset (Columbia): The Columbia dataset contains multi-view videos of persons taking a walk on a treadmill. It offers a unique perspective for GR research.
j. USF gait challenge dataset (USF Gait): The Gait challenge dataset from the University of South Florida provides gait sequences captured from different angles and distances. It is used in GR challenges and competitions [7].

5. CHALLENGES AND DISCUSSION

Earlier efforts have made an effort to approach the challenge using two angles. They see gait as an image sequence or as an individual image. The first group of methods combines entire gait contours for GR within a sole image, or gait template [40]–[47]. While many of the current gait templates [44]–[46] contain as much information as they can, important characteristics like temporal as well as fine-grained spatial information are disoriented in the compression process. The techniques in the second category take advantage of this problem by taking features straight out of the ingenious sequences of gait silhouette [48]–[51]. While these methods are better at preserving temporal information, they would significantly deteriorate when an input has a frame rate that differs from the training dataset or has discontinuous frames.

To overcome the above issue, we introduce a new approach to treat gait as a unit set of the silhouettes, utilizing a deep learning framework for identification. Our model takes characteristics from a set of gait frame, with each silhouette processed independently using CNN for local information. Set Pooling aggregates frame-level features for global information, and horizontal pyramid mapping (HPM) enhances discriminative capability, yielding a final deep-set representation.

6. CONCLUSION

This review offers a thorough examination of gait recognition (GR) systems, showcasing their diverse approaches and encountered challenges. GR, as a non-intrusive biometric modality, shows promise across security and healthcare domains. The analysis highlights silhouette-based, model-based, and deep learning methods, each with strengths and limitations. Challenges such as environmental variations, attire, and health factors pose hurdles to accurate identification. Privacy and ethical concerns also demand attention as GR technology advances. Looking ahead, opportunities for multi-modal fusion, continuous authentication, and real-world deployment strategies abound. As GR evolves, this review serves as a valuable guide for stakeholders, offering insights into current GR systems and avenues for further development. Successful GR advancement stands to bolster security, healthcare, and human-computer interaction, promising significant positive impacts in our tech-driven world. The proposed research presents a new perspective aimed at strengthening the effectiveness and efficiency of extracting the spatial as well as time-based information compared to existing methods. While conventional approaches treat gait as a template or as a sequence, this novel approach stands out by offering an innovative method to consolidate valuable spatiotemporal data from various sequences. This unique methodology will not only improve accuracy but also revolutionize cross-view gait recognition, unlike any existing gait recognition approach.

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