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Advancements in Gait Recognition: A Study on Gait Energy Images and Gait Entropy Images

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Abstract. Gait recognition is a promising biometric modality due to its non-invasive nature and difficulty to disguise. However, the performance still lacks compared to other, well established biometric modalities. This paper presents results of our study on gait recognition, focusing on the comparison between Gait Energy Images (GEI) and Gait Entropy Images (GEnI) under various conditions. Different methodologies are explored, including deep learning techniques and Vision Transformers (ViTs), for feature extraction and classification. The popular CASIA–B dataset is used to evaluate the performance across different walking conditions and entropy measures. The effectiveness of gait recognition systems in accurately identifying individuals is shown, thus highlighting the potential of GEnI in enhancing the recognition performance under varying conditions.

Keywords: Gait biometrics, GEI, Gait Entropy Image, CNN

Napredek pri prepoznavanju hoje: študija o energijskih slikah hoje in entropijskih slikah hoje

Prepoznavanje hoje je obetavna biometrična modalnost zaradi svoje neinvazivne narave in težav pri prirejanju. Zmogljivost je še vedno slabša v primerjavi z drugimi, dobro uveljavljenimi biometričnimi pristopi. Ta članek predstavlja rezultate naše študije o prepoznavanju hoje, ki se osredotoča na primerjavo med energijskimi slikami hoje (GEI) in entropijskimi slikami hoje (GEnI) v različnih pogojih. Predstavljena je analiza različnih metodologij, vključno s tehnikami globokega učenja in transformatorji vida (ViT), za pridobivanje značilk in klasifikacijo. Uporabljena je priljubljena zbirka podatkov CASIA–B za ocenjevanje zmogljivosti v različnih pogojih hoje in meritvah entropije. Prikazana je učinkovitost sistemov za prepoznavanje hoje pri natančni identifikaciji posameznikov, s čimer je poudarjen potencial GEnI pri izboljšanju učinkovitosti prepoznavanja v različnih pogojih.

1 Introduction

Each individual has its own gait which describes its unique way of walking. Unlike other biometric trait, such as facial features, iris patterns, ear shapes and fingerprints, the gait consists of several unique features. One of these features is the greater distance to the sensor, which does not require a direct interaction with a sensor such as a camera. Moreover, the inherent difficulty of altering the gait increases its reliability as a biometric identifier and reduces the possibility of fraud. Extraction of the gait data is possible even with low resolution sensors, e.g. surveillance cameras. The use of gait recognition includes the identification of individuals, which can be used in access control mechanisms, surveillance operations, and criminal investigations.

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However, the implementation of gait biometrics in real-life scenarios is hampered by several limitations and challenges. First, the environmental factors that affect the images, such as lighting changes, shadows and occlusions, can significantly distort a person's perceived gait, similar to some other biometric modalities [1], [2], [3]. Second, different camera angles can result in different appearances of the gait, even though the individual's gait signature. Common wearing modalities such as bags, coats, hats or other accessories can visually alter a person's gait and thus complicate the interpretation of gait recognition. In addition, the use of gait recognition raises issues of privacy, bias and discrimination based on physical characteristics or movement impairments.

Two methods for gait recognition are described in the literature. The first method is based on compressing silhouettes corresponding to a single gait cycle of an individual into a consolidated image, resulting in a representation of the gait features [4], [5]. Han et al. [4] introduce the Gait Energy Image (GEI) to compresses binary silhouettes extracted by background subtraction from video images into a unified representation of the gait. The second method considers the gait as a sequence of individual silhouettes, each of which is used as an input to a feature extractor [6], [7], [8], [9], [10], [11]. Newer methods are mostly based on deep learning techniques. Since their introduction in 2012 [12], Convolutional Neural Networks (CNNs) have significantly influenced image-based deep learning and are now one of the standards for gait recognition methodologies [6],

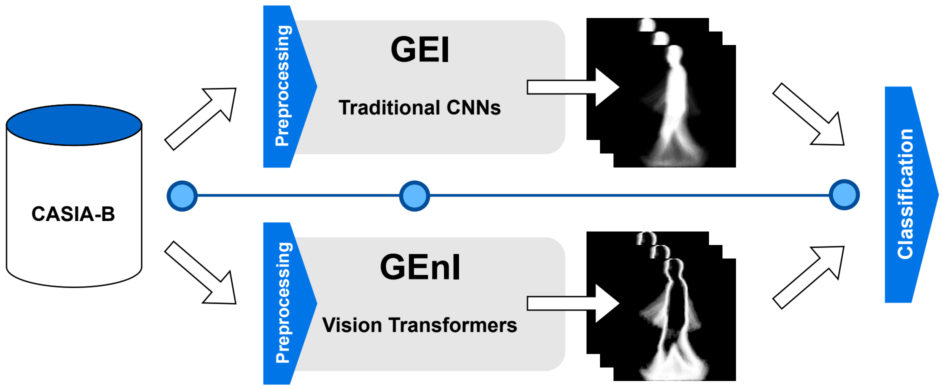


Figure 1. Overview of the proposed evaluation pipeline of two different gait recognition approaches: GEI vs. GEnI.

[7], [13], [11].

Wu et al. [13] utilize CNNs for gait feature extraction using similarity learning. GaitSet [6] propose a custom CNN framework with triplet loss for learning gait representations by treating a person's silhouette as a set. A detailed explanation of a standard gait recognition pipeline is given in previous works [9], [11]. In recent years, Vision Transformers (ViTs) have emerged as a direct challenger to CNNs for image classification tasks. Dosovitskiy et al. [14] introduce the ViT architecture. The method employs a standard transformer encoder used in natural language processing in the field of computer vision, domain and specifically targets image classification tasks. ViTs demonstrate a robust generalization capability [14]. In contrast to CNNs, ViTs require fewer computational resources for training and at the same time have better modeling capabilities.

Gait Entropy Images (GEnI) were developed as an improvement of GEI. Their use helps to accumulating the most significant motion information. GEnIs encapsulate a variance of pixel values in silhouette images throughout an entire gait cycle into one image. In this way, the motion data is preserved and remains resilient to changes in covariate conditions that affect the appearance. Bashir et al. [15] present GEnIs for capturing the motion information and exhibiting resilience to changes in the appearance. Extensive experiments show that GEnIs outperform other methods, especially in scenarios involving significant appearance changes. However, the GEnI's performance is susceptible to covariates that directly affect the gait itself.

Rokanujjaman et al. [16] investigate gait signatures by segmenting the human body into smaller fragments and examining the effectiveness of combining these fragments step by step. By using dynamically weighted entropy-based gait representations as input features, their approach outperforms both, the whole-based and the part-based gait recognition methods. The results remain consistent even with a subset of features, indicating the robustness of the proposed approach and the importance of specific parts. Jevan et al. [17] propose a novel approach utilizing the Pal and Pal Entropy (GPPE) features for gait recognition. The Principal Component Analysis (PCA) is then used to extract salient features, followed by training and testing with a Support Vector Machine (SVM). Through rigorous experiments on both the Treadmill dataset and the CASIA datasets A, B, and C, the proposed method demonstrates a superior effectiveness in gait representation, highlighting its potential for a robust individual identification.

The contributions of this paper are:

- The utility of the Gait Entropy Images (GEnI) over the traditional Gait Energy Images (GEI) in handling appearance changes in gait recognition is demonstrated.
- The performance of different entropy measures (Shannon, Renyi, Tsallis) in the context of gait recognition, with a focus on resilience to appearance changes, is evaluated.
- The efficacy of two feature extraction methods, i.e. the PCA-LDA and Vision Transformers (ViTs), in enhancing the gait recognition accuracy, is compared.
- Extensive experiments using the CASIA-B dataset to assess the gait recognition performance across various walking conditions and viewing angles are conducted.
- Insights into the implications of using ViTs for gait feature extraction, demonstrating their potential over conventional methods in certain scenarios, are provided.

2 Materials and Methods

2.1 Datasets

The dataset used was CASIA-B [18]. It contains 124 subjects, three distinct walking conditions and 11 different camera viewing angles (from 0 to 180 with an increment of 18°). The walking conditions are divided into three categories: normal walking (NM), walking while carrying a bag (BG) and walking with a coat or jacket (CL). NM has six sequences per subject, while BG and CL conditions have two sequences per subject. Each subject has a total of 110 sequences, resulting in a total number of nearly $1,118,000$ silhouette images.

The dataset is divided into a train and a test subset with the first 74 subjects used for training and the remaining 50 subjects used for testing. The first four sequences of the NM modality are assigned to the gallery, while the remaining six NM sequences together with the BG and CL sequences are assigned to the queries. In our study, no differentiation is made between the camera viewing angles.

2.2 Gait Energy Image

The standard image preprocessing methods [9], [19], [20] are applied to the dataset used. First, the image noise is filtered. Then the silhouettes for each subject are extracted in a binary format, typically using methods such as background subtraction. The images are then standardized to ensure a uniform height and horizontal alignment of all silhouettes. In the next step, the gait cycle is estimated to generate a final representation of the gait. The image-based gait features are used in the form of GEIs [4]. GEIs capture the static features of a gait sequence, for example the subject's body shape, and the dynamic aspects, including the frequency and phase variations during locomotion. The GEI representation G for a specific gait cycle is calculated using the following formula:

$$G(i,j) = \frac{1}{N}\sum_{t=1}^{N} I(i,j,t), \tag{1}$$

where N is the number of the silhouette images in the gait cycle, t is the image number at a specific point in time within the gait cycle and $I(i,j)$ is the original silhouette image with the coordinates (i,j) in a 2D image. Examples of the GEI representations for all three conditions in CASIA-B are shown in Figure 2.

(a) NM (b) BG (c) CL

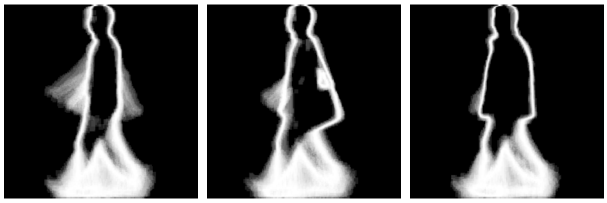
Figure 2. CASIA-B Gait Energy Images, with walking conditions divided into three categories: normal walking (NM), walking while carrying a bag (BG) and walking with a coat or jacket (CL).

2.3 Gait Entropy Image

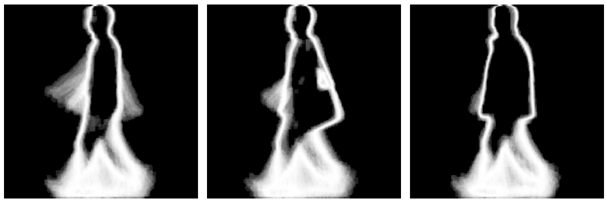
In the context of the size-normalized and centered silhouettes representing a gait cycle, the Shannon entropy [21] is calculated for each pixel in the silhouette images. It is used to quantify the uncertainty associated with a random variable. By treating the intensity value of the silhouettes at a specific pixel position as a discrete random variable, the entropy of this variable over the gait cycle is:

$$H_S(i,j) = -\sum_{k=1}^{K} p_k(i,j) \cdot log_2(p_k(i,j)), \tag{2}$$

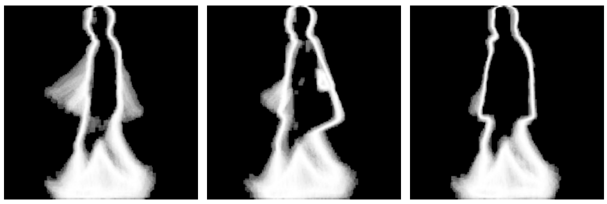
where i and j are the pixel coordinates and $p_k(i,j)$ is the probability that the pixel takes on the K-th value [15]. Since the silhouette images are binary, the number of levels used for the entropy calculation is $K = 2$.



(a) Shannon, NM (b) Shannon, BG (c) Shannon, CL



(d) Renyi ($\alpha = 0.9$), NM (e) Renyi ($\alpha = 0.9$), BG (f) Renyi ($\alpha = 0.9$), CL



(g) Tsallis ($q = 0.5$), NM (h) Tsallis ($q = 0.5$), BG (i) Tsallis ($q = 0.5$), CL

Figure 3. Resulting GEnI images for each entropy type and walking condition. In the first column normal walking (NM), in the middle column walking while carrying a bag (BG), and in the last column walking with a coat or jacket (CL). In the top row the Shannon entropy, in the middle row Renyi, and in the bottom row Tsallis entropy types.

Since the Shannon-based GEnI images show an improvement compared to the GEI images, the effects of other types of the entropy, namely the Renyi and Tsallis entropy measures, are analyzed. All three entropies are used for different problems and compared [22], [23], [24], [25], [26], [27].

Both, the Renyi and Tsallis entropy measures are generalizations of the Shannon entropy. The calculation of the Renyi-based [28] GEnI image is performed as follows:

$$H_{R,\alpha}(i,j) = \frac{1}{1-\alpha} \cdot log_2 \left(\sum_{k=1}^{K} p_k(i,j)^{\alpha} \right), \quad (3)$$

where α is the order of the entropy measure or a parameter that determines its behavior.

The Tsallis entropy [29] is calculated using the equation:

$$H_{T,q}(i,j) = \frac{1}{q-1} \cdot \left(1 - \sum_{k=1}^{K} p_k(i,j)^{q} \right), \quad (4)$$

where q is the parameter that controls the degree of non-extensivity and has a similar effect to the parameter α in the Renyi's entropy.

For each entropy, the Gait Entropy Image $G_E(i,j)$ is derived by fitting and discretizing $H(i,j)$ to ensure that its value falls in the range from 0 to 255, as given below:

$$G_E(i,j) = \frac{(H(i,j) - H_{min}) \cdot 255}{H_{max} - H_{min}}, \quad (5)$$

where H_{min} is the minimum calculated value and H_{max} is the maximum calculated value for each GEnI image. Since GEnI is calculated based on an entire gait cycle, there are no issues with the temporal alignment. The resulting GEnI images for each entropy type and walking condition are shown in Figure 3.

2.4 *Feature Extraction and Classification*

After preprocessing the initial silhouette images and converting them into GEI and GEnI images, the feature extraction and classification are performed using two feature extractors, i.e. the PCA-LDA combination and the Visual Transformer based method.

After extracting GEI and GEnI from the video sequence, the image data is converted into a one-dimensional array by stacking the image columns on top of each other. The dimensionality of this array is reduced using the Principal Component Analysis (PCA) followed by the Linear Discriminant Analysis (LDA). This process is described in detail by Lenac et al. [9] and Hofmann et al. [30]. Based on a preliminary experimental assessment of the computation time, the accuracy and our previous research, the number of components to be extracted using PCA and LDA is set to 50 and 10, respectively.

The second feature extractor is based on a self-supervised learning paradigm for learning discriminative gait features. The DINO method is used, showing promising results on various computer vision tasks such as image classification and retrieval [31]. To adapt DINO to the gait-specific data, the input sizes and augmentations used in training are modified. DINO demonstrates the ability to segment objects in the foreground. This is important in gait recognition scenarios where people stand out from the background. Given the limited data in gait datasets for training the ViT models from scratch, a fine-tuning strategy is applied where DINO is first trained on the ImageNet dataset and then fine-tuned for the gait data. With this approach, DINO can be used as a feature extractor to generate discriminative features for subsequent classification tasks. A small ViT model set up by Touvron et al. [32], with a patch size of 8, is used.

PCA is applied to the training set. Both the gallery and query are transformed into 50 features per image. LDA is used to learn class-conditional densities from the transformed gallery and further transforms the query into 10 features per image, which are used for the classification. The DINO feature extractor is trained with the images from the training subsets. Then the gait feature for the gallery and query images is extracted and used for the classification. The classification is performed using the k-nearest neighbors (kNN) algorithm.

3 Results and Discussion

The tests are performed with GEI and GEnI images. For GEnI images, the Shannon, Renyi and Tsallis entropies are used. For both entropies, different values of α and q are examined, ranging from 0.1 to 5.0. Table 1 compares the results of the GEI and GEnI preprocessing approaches with two feature extraction extractor pipelines for all three gait walking conditions.

GEI outperforms all GEnI approaches with the PCA-LDA features. With ViT-8 it achieves the best result for the BG condition. Tsallis GEnI with $q = 1.5$ achieves the highest accuracy for the NM conditions with ViT-8. Renyi with $\alpha = 0.9$ proves to be the best for both the CL conditions and overall accuracy with ViT-8.

Comparing the results between the entropies, shows that the Shannon entropy does not perform best in any of the categories. Tsallis performs best with PCA-LDA and Renyi with ViT-8. In the overall ranking, GEnI based on the Shannon entropy performs better than Renyi on three different α values and better than Tsallis on two different q values for the PCA-LDA feature extractor. ViT-8 strongly favors Renyi and Tsallis compared to the Shannon entropy and even GEI.

4 Conclusion

Our analysis reveals that Gait Energy Images (GEI) excel when coupled with the traditional feature extraction methods such as PCA-LDA, affirming their compatibility with the established analytical frameworks. Oppositely, Vision Transformers (ViTs) demonstrate a notable preference for Gait Entropy Images (GEnI) processed with the Renyi and Tsallis entropies. This distinction suggests that ViTs' advanced learning capabilities, particularly in recognizing and distinguishing shapes, are better leveraged by the nuanced information

Image type	α, q	PCA-LDA				ViT-8			
		NM	BG	CL	Overall	NM	BG	CL	Overall
GEI		**90.45**	**66.48**	**40.82**	**65.92**	99.18	**82.24**	25.27	68.90
GEnI: Shannon		88.27	55.83	35.91	60.01	99.18	77.86	31.09	69.38
GEnI: Renyi	0.5	85.73	57.93	35.82	59.82	98.73	79.04	31.91	69.89
	0.7	87.91	57.66	36.09	60.55	98.73	*79.22*	32.09	70.01
	0.9	87.91	55.75	36.00	59.88	98.91	78.68	**32.82**	**70.14**
	1.5	87.64	53.37	33.18	58.07	99.18	78.14	31.09	69.47
GEnI: Tsallis	0.5	86.91	*58.93*	36.27	*60.70*	98.55	79.04	32.36	69.98
	0.7	88.27	57.20	*36.45*	60.64	98.82	78.68	32.09	69.87
	0.9	87.91	55.75	36.09	59.92	99.00	78.87	32.27	70.05
	1.5	*88.36*	54.47	35.64	59.49	**99.27**	78.32	31.82	69.80

Table 1. Accuracy scores for both approaches for the feature extraction on GEI and GEnI input images for all walking conditions of CASIA-B, where NM, BG and CL denote normal walking, walking while carrying a bag, and walking with a coat or jacket respectively.

captured by the Renyi and Tsallis entropies. By providing a detailed representation of the variability around the silhouette of a person, these entropies enhance the model's ability to discern subtle differences in the gait patterns. Besides highlighting the evolving landscape of the gait recognition technologies, this study also shows a promising direction for a future research in optimizing feature extraction techniques to leverage the strengths of contemporary deep learning models.

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