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Machine learning models and methods for human gait recognition

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ABSTRACT

The paper explores the challenge of human identification through gait recognition within biometric identification systems. It outlines the essential criteria for human biometric features, discusses primary biometric characteristics, and their application in biometric identification systems. The paper also examines the feasibility of utilizing gait as a biometric identifier, emphasizing its advantages, such as not requiring the upfront provision of personal biometric information and specialized equipment. The authors conduct an analysis of existing scientific literature in the field of gait recognition, categorizing gait recognition methods into template-based and non-template-based approaches. Throughout their research, they identify the key issues and challenges that researchers face in this domain, along with the prevailing trends in human gait recognition within biometric identification systems. Additionally, the paper introduces a method for person identification based on gait, utilizing the Histogram of Oriented Gradients and the Sum Variance Haralick texture features. It involves transforming input video into a series of images depicting the gait silhouette, creating a Gait Energy Image (GEI) by combining these gait silhouettes throughout a gait cycle, and translating the GEI into the Gait Gradient Magnitude Image (GGMI). The subsequent step involves extracting recommended gait characteristics from the GGMIs of participants included in a dataset. To preprocess the collected characteristics, Principal Component Analysis (PCA) is applied, reducing the dimensions that may negatively impact classification robustness, thereby enhancing overall performance. In the final step, a K-Nearest Neighbors (KNN) classifier is employed to categorize the characteristics obtained from a specific dataset. The proposed novel feature vector in the paper demonstrates increased reliability and effectively captures spatial variations in gait patterns. Notably, it reduces the dimensionality of the feature vector from 3780×1 to 63×1, resulting in decreased computational complexity in the gait recognition system. Experimental evaluations on the CASIA A and CASIA B datasets reveal that the proposed approach outperforms other HOG-based methods in most scenarios, with the exception of situations involving frontal images.

Keywords: Gait recognition; histogram of oriented gradients; haralick texture features; principal component analysis; classification; gait patterns; computer vision

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INTRODUCTION, FORMULATION OF THE PROBLEM

Biometry refers to a distinct attribute or personal feature that endures consistently and has the capacity to uniquely identify an individual. This technology finds use in several domains, including but not limited to forensics, access control, workforce monitoring, and shoplifter detection [1].

Historically, biometric modalities such as fingerprint, face, and iris have been widely used [2, 3], [4]. Nevertheless, there are several limitations that restrict its use in certain circumstances.

One limitation is that many biometric methods need the active participation and collaboration of the individual being recognized, which may not be ideal in surveillance contexts. Furthermore, it is important to note that the extraction of these biometrics is not feasible by remote means, since the information pertaining to these biometrics is either inaccessible or significantly compromised when obtained from a distance [5].

An alternate option arises in the form of gait, which involves a multifaceted array of biomechanical dynamics that are coordinated by the central nervous system and occur entirely at the subconscious level [6].

The research results from neurophysiology and psychology provide support for the notion that gait has distinct characteristics that may be used to differentiate and identify individuals based on their walking patterns [7, 8], [9]. It is noteworthy that individuals possess the capacity to perceive a person whom they are acquainted with from afar, even when that person is moving in the other direction. This ability is attributed to the distinctive gait features shown by the people in question.

In contrast to other biometric modalities, gait has many distinct benefits. Firstly, gait is unobtrusive, meaning that it does not need direct physical contact with the individual being identified. Additionally, gait may be captured from a considerable distance, even before a good view of the individual's face is attainable. Furthermore, gait data can be gathered during nighttime using infrared cameras, thus enhancing its versatility and applicability [10].

Over the course of many decades, there has been an increasing need for effective monitoring programs with the objective of safeguarding social security. Nevertheless, the surveillance films they have obtained may exhibit substandard quality, such as low resolution and inadequate lighting, among other factors. Moreover, the monitor entities possess the ability to obscure a significant portion of their typical biometric features via the utilization of masks, glasses, or gloves. When considering various biometric options, gait detection using machine perception emerges as a potentially superior alternative for the majority of surveillance systems [11].

As previously stated gait has the ability to function well in an unrestricted environment and may be quantified remotely without the need for physical touch or close-range sensing. The aforementioned qualities make gait particularly appealing for the purpose of human identification. Furthermore, it should be noted that many surveillance systems are limited in their ability to capture high-resolution videos in challenging lighting conditions. Consequently, gait recognition emerges as a viable alternative for automated identification [12].

Furthermore, the analysis of gait may be performed by extracting information from either a series of successive frames or a single static frame. Therefore, the use of gait as a biometric for deploying surveillance systems is comparatively more convenient than other biometric methods. For instance, this technology may be readily implemented at various street intersections or other locations with significant traffic volume [13].

Gait recognition encompasses three distinct methodologies that vary dependent on the used method for recording gait data. There are gait identification systems that rely on machine vision, floor sensors, and wearable sensors [14].

Machine vision technology which relies on the use of computer algorithms to interpret and analyze visual data is used in many applications. Typically, the biometric equipment used in this methodology comprises a collection of digital cameras equipped with suitable lenses to acquire the gait data. In this context, a variety of methodologies are used, including background segmentation, pre-processing, subsequent feature extraction, and classification, with the aim of discerning the identity of a person. The majority of the current gait detection techniques are reliant on machine vision. One significant advantage of using this approach is its ability to extract a comprehensive range of gait data from the recorded video, including parameters such as stride, cadence, step length, area, and inter-segment distances. Furthermore, the involvement of individuals is not required in these approaches [14].

The system relies on floor sensors for its operation. In this particular methodology, the sensors are strategically positioned on a mat that spans over the floor surface. This feature renders it appropriate for the management of entry to several structures, including but not limited to buildings, workplaces, residences, and other locations where ensuring security is of utmost importance. The ground response force, also known as the force exerted on the ground when a human walks on a mat, is measured. Hence, the implementation of this approach may be facilitated by the use of access control systems, such as those installed at the entrance of a building. This approach has the capability to provide both location and identification data. Only a limited number of gait characteristics may be derived by the use of this approach, including cadence, stride length, maximum duration of heel strike, and similar parameters [15].

The wearable sensor-based approach is the most current way compared to the previously described approaches. This approach involves the use of sensors affixed to several locations on an individual's body, including the hands, legs, waist, and feet, to capture and document their bodily movements. These sensors are used to measure numerous elements, such as acceleration, rotation, force while walking, etc.

One notable benefit of using gait as a biometric modality is in its unobtrusiveness. In contrast, the wearable sensor-based approach fails to meet this criterion, since it requires the active participation of individuals in order to gather gait data. In addition, it should be noted that the expenses associated with the acquisition of sensors used for the purpose of quantifying ground reaction force in the floor sensor-based methodology are substantial [16].

The selected methodology for gait detection in this work is the machine vision-based technique, which is not affected by the aforementioned setbacks. Significant advancements have been made in vision-based gait recognition methodologies over the course of the last twenty years. However, several restrictions exist with regards to the actual implementation of gait analysis.

In recent times, there has been a notable shift in gait detection research towards the development of a gait representation that has the potential to extract substantial information even in unpredictable circumstances. Furthermore, the efficacy of any gait identification technique is mostly contingent upon the nature and caliber of the extracted gait characteristics.

One of the primary obstacles faced by the gait recognition system pertains to enhancing its performance via the use of a unique low-dimensional feature vector [17].

Thus, **the purpose of this study** is to develop a framework that considers the low-dimensional characteristics that have the ability to accurately capture the spatial, gradient, and texture information in order to achieve efficient and resilient detection of human gait.

1. LITERATURE REVIEW

Gait identification approaches may be roughly classified into two groups: model-based approach and appearance-based approach [17]. The classification is derived from the particular approach used for the identification and extraction of unique characteristics associated with an individual's gait.

Model-based approach includes a collection of methodologies that depend on the use of mathematical models for the purpose of analyzing and resolving issues. Model-based strategies are used to depict and study the movement of the human body, specifically the gait sequences. Various methodologies are used to examine the kinematics of an individual's joints, with the aim of quantifying diverse gait characteristics. These parameters include, but are not limited to, direction, hip, knee, and ankle movements, as well as hand movement. Various approaches have been used to generate a physical or anatomical model derived from gait film. The computational expense associated with these methodologies is often substantial as a result of the need to model and monitor the physiological state of the individual. Moreover, there is a need for images with high resolution [17].

Conversely, appearance-based methodologies include doing operations directly on images of gait without depending on an explicit model. The use of these methodologies is often preferred over model-based techniques owing to their decreased computational complexity [17]. Various appearance-based gait recognition feature sets are shown in Table 1.

Table 1. **Overview of gait recognition sets used in appearance-based gait recognition**

Paper	Features
[18, 19]	The dimensions of various body components in terms of length and height
[20, 21],[22]	The widths of silhouette rows
[23]	The Fourier descriptors pertaining to the silhouette outline
[24]	The average silhouette of gait energy image (GEI)
[25, 26]	Energy expenditure associated with human gait
[27]	Image representation that captures the distribution and intensity of gradients within an image
[28]	Gait entropy
[29]	A histogram depicting the distribution of normal vectors along the silhouette outline

Source: **compiled by the authors**

1.1. Detailed review of appearance-based methods

In order to acquire knowledge on the current state of research on human gait detection, a subsequent literature survey is presented, offering insights into several strategies for human identification that include statistical shape analysis.

Various methods have been developed to effectively capture the inherent characteristics of silhouettes in a static manner. In paper [30] authors successfully acquired the measurements of the width of each silhouette and then used a hidden Markov model to construct a model based on these measurements. In paper [31], authors retrieved the silhouette width vector of the leg area. In their study, in paper [32], authors conducted a study on the procrustes shape analysis method, which involves extracting gait properties from edge image components. In their study [33], authors used various approaches to identify and analyze a range of factors. The front view is the most appropriate perspective for using this procedure, since considering a side view may result in inaccurate measurements for some characteristics.

An alternative method for transforming the gait silhouette involves the computation of an average profile throughout an entire gait cycle. Authors of paper [34] applied the average silhouette, followed by the utilization of the idea known as GEI [35]. This depiction exhibits greater resilience against slight phase fluctuations and noise. The aforementioned description was suggested as a means of enhancing many variants that have since evolved into the current paradigm in gait characterization. Similarly, researchers have also developed the gait flow image [36], the gait entropy image [37], and the masked GEI [38].

Numerous methodologies have been developed with the aim of capturing both the static and dynamic properties associated with silhouettes and GEIs. Authors of paper [39] have introduced a novel methodology for gait detection that involves the use of manually extracted and annotated silhouettes. The outcomes of the many body components possessing distinct discriminatory abilities are aggregated into a shared distance measure, which is used to assess the similarity of gait sequences. In their study [40], authors have generated a gait entropy image by preserving the entropy statistics derived from the arbitrary pixel values in a silhouette gait sequence.

The appearance-based techniques are effective in accurately representing the physical structure of a person. The body form has been shown to be a discriminatory factor in the majority of the approaches used. Several feature extraction strategies reported in the literature seem to effectively capture this information. Furthermore, these qualities also include temporal information.

Instead of using a two-dimensional picture, several investigations choose to use depth images. Motion capture systems, such as the Microsoft Kinect, are used for the acquisition of depth pictures. The evaluation of gait energy volume, namely the average silhouette volumes derived from depth photographs, was conducted in study [32]. In their seminal work [34], authors introduced a novel approach for representing depth imaging by using the Histogram of Oriented Gradients (HOG) technique.

Deep learning algorithms have garnered significant interest from the computer vision community in recent years. The reason for this phenomenon is because deep learning models have the ability to acquire several levels of feature hierarchies by generating high-level features based on low-level characteristics [34]. Several recent research have shown encouraging outcomes when using deep learning techniques across several applications. In paper [32], authors developed a multilayered back-propagation method using Artificial Neural Network for the purpose of gait categorization. In study [24], authors used the utilization of GEI (Gait Energy Image) as an input for a Convolutional Neural Network (CNN) known as GEINet, which was specifically developed for the purpose of gait detection. In paper [31], authors have proposed a novel Deep Convolutional Neural Network (DCNN) architecture specifically designed for the purpose of gait identification. In their study [37], authors successfully used deterministic learning techniques to predict the frame-to-frame gait dynamics of many participants using radial basis function neural networks.

a b c

Fig. 1. **Example of gait detection:**
a – Background image; b – original image; c – extracted silhouette
***Source:* compiled by the [32]**

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1.2 Review of appearance-based methods with HOG descriptors usage

In recent years, the Histogram of Oriented Gradients (HOG) method has been used in many appearance-based methodologies for human identification, specifically focusing on gait characteristics.

In their study [23], authors used the Histogram of Oriented Gradients (HOG) technique to generate a collection of characteristics that include both temporal and spatial information derived from a gait cycle.

In a previous study [41], author used the Histogram of Oriented Gradients (HOG) technique to get a motion history picture that is averaged across time intervals.

By using a combination of Histogram of Oriented Gradients (HOG) and motion history photos, this methodology has the potential to mitigate the impact of fluctuations in gait speed, allowing for the extraction of distinct gait cycle phases.

In their study [42], authors proposed a technique known as the histogram of weighted local directions. This approach involves the generation of a histogram that is based on the local gradient directions. The resulting histogram is then used as a feature vector for the purpose of gait recognition.

In a study [37], the authors extracted Histogram of Oriented Gradients (HOG) from motion history images and provided evidence to suggest that HOG is less effective at capturing dynamic motions compared to static movements.

The notion of the gradient histogram energy picture, introduced in [43], is used to collect edge information inside the silhouette for the purpose of gait detection.

In their study [44], authors used a composite approach including binarized statistical characteristics, motion history picture, and HOG to enhance the efficacy of a gait detection system.

1.3 Review of silhouette extraction techniques

Silhouette extraction is the prevailing data pre-processing technique used in vision-based gait identification. The use of human gait silhouette images has been favored by several researches over color images due to the redundancy of backdrop information and clothing color in relation to human gait detection [45].

Therefore, the primary objective in gait identification is the transformation of gait photos into gait silhouette images.

One often used method involves the utilization of backdrop subtraction, wherein the gait silhouette is discerned as a dynamic entity within the given environment.

Numerous methodologies have been devised in previous research endeavors to address the task of backdrop subtraction.

Several commonly used methods in the field of computer vision for background subtraction include frame differencing [26], background estimation by averaging n frames [27], and Gaussian average computation [28], among others.

Subsequently, a series of procedures, including de-noising, post-processing, and normalizing, are implemented in order to get gait silhouette pictures. Figure 1 displays both an original picture sample and the corresponding silhouette image that has been extracted.

The majority of benchmark databases consist of topic data represented in the form of silhouette images.

1.4. Review of Gait Energy Image representation

Many appearance-based approaches favor the use of a two-dimensional representation called Gait Energy Image (GEI) for analyzing gait cycles [29]. Each of the GEI templates is constructed according to the following approach:

1) obtaining the silhouettes of a figure from a single gait cycle;
2) center alignment and resizing silhouettes to a predetermined size;
3) combination of resized silhouettes of a certain gait cycle in order to generate the gait template.

The Gait Energy picture (GEI) refers to the representation of human gait via a grayscale picture.

This image is created by computing the average of the silhouettes captured across a complete gait cycle.

The computation is performed in the following manner:

$$G(i,j) = \frac{1}{N}\sum_{f=1}^{N} S(i,j,f), \qquad (1)$$

where N denotes the overall count of frames throughout a gait cycle, S refers to the silhouette picture, while i and j represent the spatial coordinates of the image. Additionally, f indicates the specific frame number inside the gait cycle [30]. Fig. 2 depicts a representative representation of the gait cycle and gait energy expenditure index (GEI).

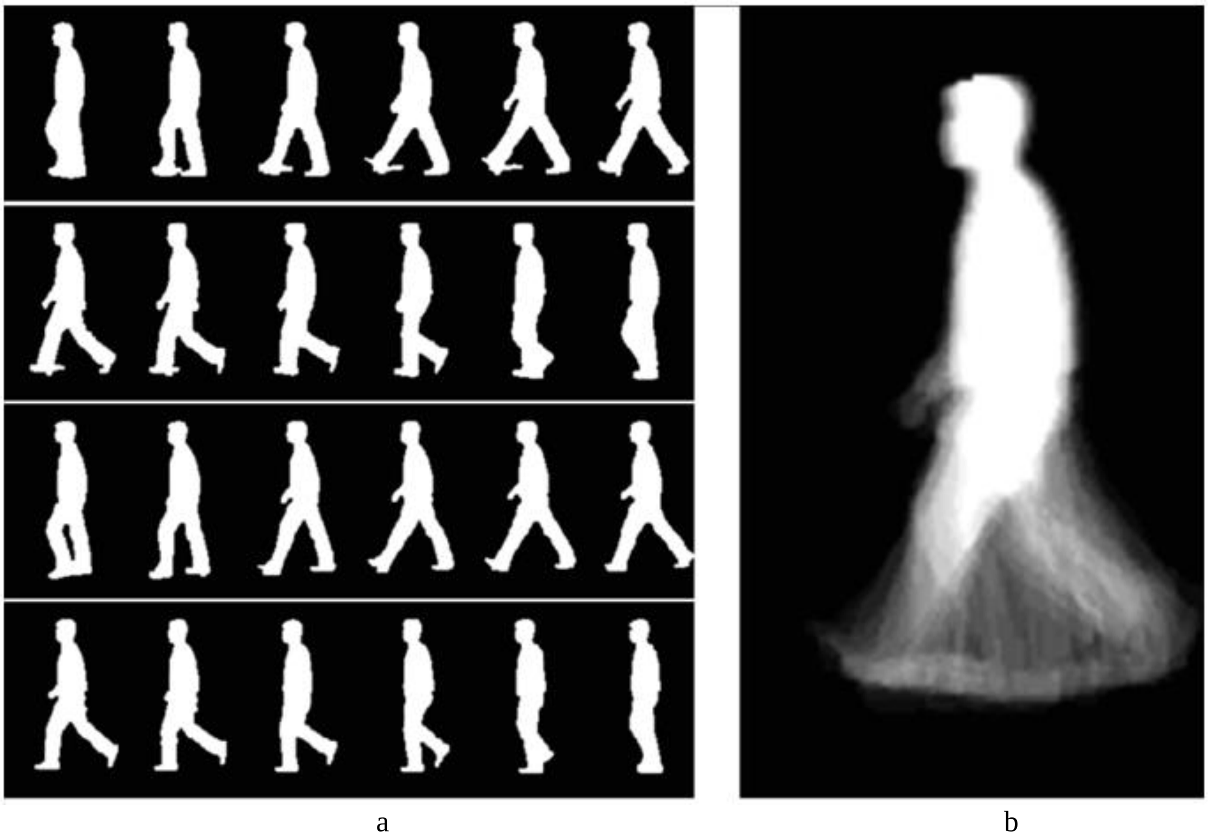

Fig. 2. **Sample image representing gait cycle GEI:**
a – Gait images of a cicle; b – Gait energy image (GEI)

Source: **compiled by the [32]**

Pixels with higher intensity are associated with the non-moving sections of the body, namely the upper area. This segment contains important body contour data that may be useful for identification purposes. However, it is also subject to the impact of variables.

Pixels with lower intensity are found in the active regions of the body, namely the lower area. This portion of the gait energy image (GEI) is particularly advantageous for identification purposes and is not affected by variables such as clothing and carrying circumstances.

Fig. 3 displays the graphical depiction of the pixel value intensity in a GEI. One advantage of using GEI is its ability to significantly lower the dimensionality of features when compared to the whole gait sequence.

As a result, this reduction in dimensionality also leads to a drop in processing cost.

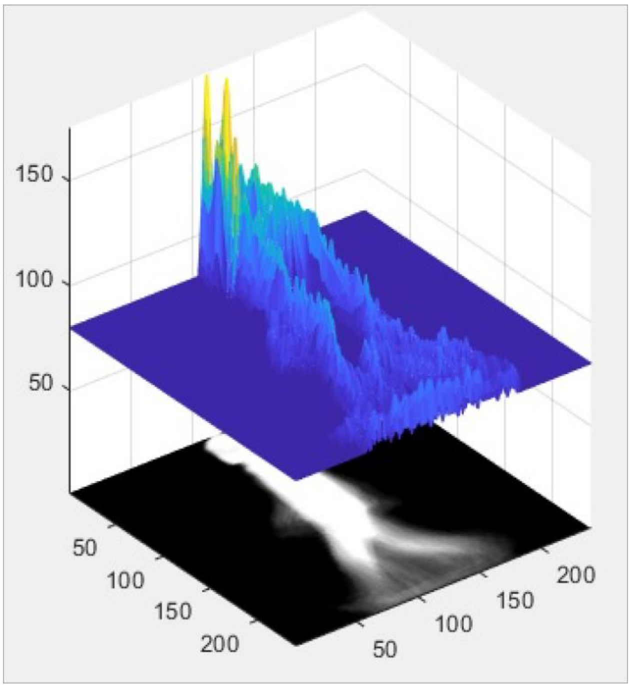

Fig. 3. **The pictorial representation of the intensity values of the pixels in GEI**
Source: **compiled by the [32]**

1.5. The result of the literature review

The results drawn from the literature review on the gait recognition system are as follows:

− in recent years, there has been a growing focus on enhancing and broadening individual recognition frameworks. Gait recognition is an attractive technique from a surveillance perspective due to its ability to identify persons from a distance by analyzing their walking patterns. Gait is a distinctive behavioral biometric characteristic that may be assessed without the need for physical touch. This characteristic makes it advantageous in the context of surveillance applications;

− the predominant methodologies used in contemporary gait recognition research mostly revolve on appearance-based techniques, owing to their inherent simplicity and superior rates of recognition. Primarily, their emphasis is on providing resolutions for practical situations in which alterations in appearance must be confronted. In many scenarios involving gait challenges, it is common for individuals to exhibit appearance alterations in real-world applications. These alterations often arise due to factors such as variations in perspective, walking velocity, attire, and the act of carrying objects;

− the Histogram of Oriented Gradients (HOG) is well recognized as a robust descriptor for analyzing greyscale images. Although Histogram of Oriented Gradients (HOG) has been widely used for gait identification in recent studies, it is worth noting that the feature vector size utilized in these research is notably substantial. The inclusion of these characteristics with a large number of dimensions will therefore result in an expansion of the search space. Moreover, the inclusion of this feature will result in an escalation of the algorithm's run-time complexity, exhibiting exponential growth as the dimensionality increases.

2. PROPOSED FRAMEWORK

It is clear from the research that HOG is an effective feature descriptor that is employed in gait recognition systems [39]. When extracting the local shape information from a window or area of interest in a gait picture, the HOG descriptor is the tool of choice. Even while HOG is employed for gait identification in some of the more recent research [33], the size of the feature vector that is utilized in those works is exceedingly big. The search space is subsequently expanded as a result of these high-dimensional properties. In addition to this, it contributes to an increase in the run-time complexity of the gait recognition system, which develops at a rate that is linearly proportional to the rise in dimension.

In addition, if you keep the number of training samples constant, your prediction power will decrease as the complexity of the data grows. It is required to design an effective strategy that boosts the effectiveness of the gait recognition system while simultaneously reducing the amount of HOG characteristics in order to get over this obstacle.

The use of HOG in conjunction with the Haralick features was the key to success in this endeavor. In addition, the texture is one of the essential biometric properties that can be found in any picture. This property is always present. The purpose of this is to measure and identify areas of interest within a picture. In conjunction with HOG, it is possible to derive the most distinctive low-dimensional feature vector that is also capable of identifying people in a one-of-a-kind fashion.

Figure 4 presents an overview of the structure that will be used for the proposed gait recognition method. It may be broken down into four distinct steps.

First, the video of the gait is transformed into a series of photos showing the gait silhouette. The GEI is created by combining these gait silhouettes throughout the course of a gait cycle. The GEI is then translated into the Gait Gradient Magnitude Image (GGMI).

The second step is to derive the recommended gait characteristics from the GGMIs of the participants that are included in a given dataset.

Thirdly, in order to pre-process the characteristics that were retrieved, Principal Component Analysis (PCA) is used. It does this by decreasing the dimensions that have a detrimental effect on the robustness of the classification, which in turn leads to an improvement in performance.

In the last step, the KNN classifier is used to assign categories to the characteristics that were collected from a particular dataset.

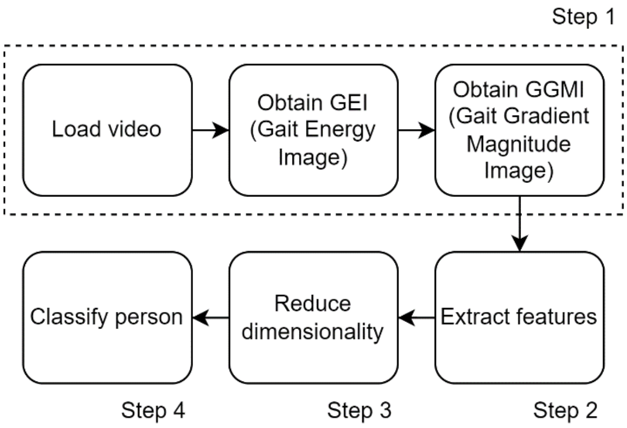

Fig. 4. **The structure of proposed approach**
Source: **compiled by the authors**

When applied to GEI, the Gaussian filter [64] and then a Sobel edge detector [35] produce GGMI as a result. While the Gaussian filtering eliminates the detail and noise from the GEI, a pair of 3 x 3 kernels of the Sobel operator exposes the areas of high spatial frequency that correspond to edges [36].

When used to GEI, a Gaussian filter, followed by a Sobel edge detector, considerably reduces the amount of information that has to be processed and, as a result, removes the information that is considered to be of less significance. In the meanwhile, it keeps all of the essential structural characteristics of GEI intact.

The GGMI template is readied for the feature extraction process as part of this operation. Following the removal of GEI from a gait cycle, the information is further processed to produce GGMI. The approach that was used was developed with the intention of obtaining the magnitude or edge information from the subject's GEI. Figure 5 presents several example GGMIs for the usual walking situation, displaying them from a variety of perspectives.

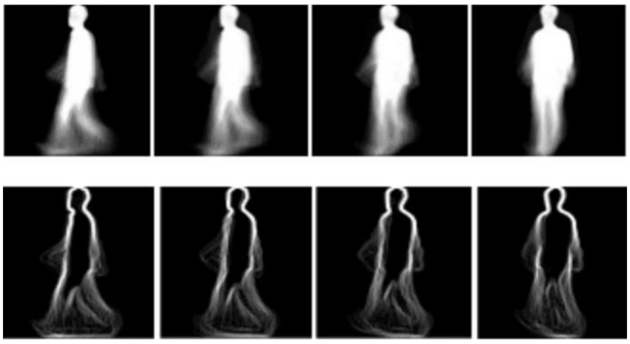

Fig. 5. **Sample GEI and GGMI for various views**
Source: **compiled by the authors**

2.1. Usage of Histogram of Oriented Gradients

The use of HOG in appearance-based approaches has been shown in recent research to increase the performance of gait recognition [39]. HOG is a global descriptor that was presented in paper [40]. It depicts the distribution of edge directions as well as intensity gradients. In order to calculate the HOG feature, the gradient vector that is present at each pixel in the GGMI is employed in the beginning.

The following is a list of the gradient operators of the first order that are used in order to extract the magnitudes of the horizontal and vertical gradients:

$f_{xdir} = [-1\ 0\ 1]$, and $f_{ydir} = [-1\ 0\ 1]^T$.

After that, the horizontal and vertical gradient pictures are merged in order to determine the magnitude and direction of the gradient. After that, the histograms of the cells are formed. The picture is broken up into smaller sections that are connected with one another and are termed cells. The next thing that has to be done is to produce a histogram of the gradients that are present in these cells.

The intensity of the pixels in the direction of the gradient is used to pick a bin, and the intensity of the pixels in the magnitude of the gradient is used to select the vote, which determines which value is placed in the bin. This vote is cast by every pixel that is present within the cell, and it is used to generate HOG. Due to the fact that the cells overlap in the middle of their respective areas, each cell contributes to the final feature vector more than once.

A histogram of the gradient directions is constructed for each and every pixel included inside each cell. The HOG descriptor is formed by concatenating all of these histograms together. The gradient values that are so produced are then locally normalized, which means that in order to account for the differences in contrast and illumination, they are normalized across each cell individually.

In order to get the feature vector, 9 rectangular cells of similar size are employed, and inside each cell, 7 bin histograms are created. The bins have a degree that varies from 0 to 0 and a range that varies from $-\pi$ to π, with a range of $51.43°$ for each bin.

The number of cells and histogram bins both have an impact on the total number of features. As a result, a 63-by-1-dimensional HOG description is created by concatenating the 9 cell histograms that each include 7 bins. The HOG is used in this manner in order to reflect the characteristics of each GGMI.

This work makes use of the HOG descriptor to allow a better characterization of the appearances and forms of the subjects based on the distribution of the local intensity gradients with the oriented directions. This is accomplished by applying the HOG descriptor to the oriented directions of the local intensity gradients.

2.2. Usage of Haralick features

When doing texture analysis using Haralick features, the first step is to calculate the Gray-Level Co-occurrence Matrix (GLCM) [41]. This matrix should have the number of gray levels that are required for the study.

One of the most well-known techniques for extracting features from textures is called GLCM. It is used to estimate the second-order statistical characteristics of the pictures, and it gives important data on the relative position of the surrounding pixels in a gait image. In addition, it is used to estimate the statistical aspects of the images.

Therefore, the likelihood that a pixel with value g will be discovered next to a pixel with value h is

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assigned to each item in the GLCM table. An element $p(g,h)$ of the co-occurrence matrix is calculated by the relative frequencies in which two pixels, one with gray level g and the other with gray level h, are separated by a distance d and occur in a direction indicated by the angle θ:

$$p(g,h) = \sum_{x=1}^{N_g}\sum_{y=1}^{N_g}\begin{cases}1 \; if \; I(x,y) = g \; and \; I(x+dx, y+dy) = h \\ 0 \; otherwise\end{cases}, \quad (2)$$

where N_g is the number of gray levels in the GGMI, while dx and dy specify the distance between the pixel of interest and its neighbor.

Multiple GLCMs may be calculated for distinct values at 0°, 45°, 90°, and 135°, each of which can accurately portray the spatial connection between surrounding pixels and lead to robust texture characteristics of GGMI pictures.

The Gray-Level Co-occurrence Matrix (GLCM) of the Gait Gradient Magnitude Image (GGMI) with a dimension of $N_g \times N_g$ may be formally described as:

$$P = \begin{bmatrix} p(1,1) & p(1,2) & \dots & p(1,N_g) \\ p(2,1) & p(2,2) & \dots & p(2,N_g) \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ p(N_g,1) & p(N_g,2) & \dots & p(N_g,N_g) \end{bmatrix}. \quad (3)$$

The normalized GLCM is computed as:

$$P = \frac{p(g,h)}{\sum_{g=1}^{N_g}\sum_{h=1}^{N_g} p(g,h)}. \quad (4)$$

The subsequent procedure involves the computation of Haralick texture features derived from the normalized Gray-Level Co-occurrence Matrix (GLCM) of the Gray-Level Gradient Magnitude Image (GGMI).

The Haralick features [40] include a set of 14 statistical entities that serve to characterize the textural attributes derived from P.

The extraction and calculation of this texture descriptor is performed in four directions. The values of θ are $0°$, $45°$, $90°$, and $135°$.

Let x and y denote the respective row and column coordinates of an item inside the co-occurrence matrix.

Then $p_x(g)$ is computed as:

$$p_x(g) = \sum_{h=1}^{N_g} p(g,h). \quad (5)$$

Accordingly, $p_y(h)$ is computed as:

$$p_y(h) = \sum_{g=1}^{N_g} p(g,h). \quad (6)$$

Moreover, $P_{x+y}(i)$ is the probability of the sum of coordinates in a co-occurrence matrix being equal to $x + y$, as defined in the following manner:

$$p_{x+y}(r) = \sum_{g=1}^{N_g}\sum_{h=1}^{N_g} p(g,h) \quad (7)$$

$$where \; r = g + h \; with \; r = 2,3,\dots,2N_g.$$

This research only focuses on the total variance (f_{sv}) feature throughout the feature extraction procedure. In order to calculate f_{sv}, it is necessary to compute the sum average (f_{sa}) Haralick texture descriptor. The sum average is defined as:

$$f_{sa} = \sum_{r=2}^{2N_g} r p_{x+y}(r). \quad (8)$$

Accordingly, sum variance is defined as:

$$f_{sv} = \sum\nolimits_{r=2}^{2N_g} (r - f_{sa})^2 p_{x+y}(r). \quad (9)$$

2.2 Features extraction step

The feature extraction approach used in our study incorporates the evaluation of discriminative features, namely the Histogram of Oriented Gradients (HOG) and the Haralick features.

The process of feature extraction involves the following steps:

1) the GGMI should be divided into nine cells of similar size;
2) the HOG characteristics are computed from nine distinct cells of the GGMI;
3) compute the sum variance Haralick features for the nine distinct cells;
4) in order to calculate the product, the sum variance feature of a cell is multiplied by the HOG characteristics of the same cell:
5) execute Step 4 on each of the nine cells inside the GGMI;
6) To generate a concatenated representation of the feature values, the values collected from 9 cells are combined together.

The gradient images g_{xdir} and g_{ydir} are produced from the convolution of GGMI using the gradient operators f_{xdir} and f_{ydir}. The subsequent procedure involves acquiring two distinct pictures, namely the magnitude image (mag_{image}) and the orientation image ($orient_{image}$), derived from the gradient images.

Assume that the entire quantity of bins, denoted as B, is equal to 7. In this context, the pictures representing both magnitude and orientation are partitioned into nine cells using the R-HOG method. The pixels contained inside each cell are transformed into column vectors, denoted as $V_{mag_{image}}$ and $V_{orient_{image}}$, representing the magnitude and orientation images, respectively.

To construct the histogram, we examine a set of seven orientation bins within the range of $-\pi$ to π. Each bin is given a value of $2 \times \pi/B$. The algorithm is executed on the magnitude and orientation pictures within a specified range during each cycle. In this context, the presence of each pixel inside the orientation picture of a cell is examined to see whether it falls within a certain range of orientation.

If the value is inside the specified range, the appropriate pixel in the magnitude picture is accumulated and saved. A total of seven values are acquired for each individual cell. Therefore, a feature vector f_g with dimensions 63×1 is acquired. The acquisition of f_n is a normalized process.

Subsequently, the Gray-Level Co-occurrence Matrix (GLCM) is calculated for each individual cell. This is then followed by the calculation of the sum variance texture descriptor in four distinct directions, denoted as θ (namely, 0°, 45°, 90°, and 135°). Then, the average value of the four directions, denoted as f_{sv}, is derived. The product of the sum variance value acquired for a specific cell and the feature vector f_n of that cell is calculated. Finally, the characteristics of all nine cells are combined to form the feature vector, denoted as f.

3. EXPERIMENTAL RESULTS

The templates used in the experiments, namely GEI (Gait Energy Image) and GGMI (Gait Motion Image), possess dimensions of 240×240. The GGMI template consists of nine cells, which are split with a 50% overlap. Therefore, the dimensions of each cell are 120×120. A set of seven values is acquired from each cell measuring 120×120, corresponding to the total number of bins being seven. Finally, the values of seven bins consisting of nine cells each are combined to form a feature vector f with dimensions of 63×1.

The HOG descriptor calculates features based on the gradient orientations' distribution. The gradients of a picture possess significant value, since they exhibit huge magnitudes in the vicinity of corners and edges. The corners and edges of an object include a greater amount of informative content on its shape compared to its flat parts. Therefore, the use of GGMI results in the enhancement of prominent edges, therefore facilitating the improvement in the efficiency of a gait recognition system.

The majority of previous studies have focused on using 9 bins for each cell. However, this research explores the use of a variable number of bins in order to achieve improved identification accuracy while minimizing the amount of features required. The research conducted experiments using a range of bin quantities, namely 4, 5, 6, 7, 8, and 9 bins per cell. Consequently, the research demonstrates a high level of accuracy in recognizing patterns when using a system with 7 bins, while seeing a little improvement in performance when employing systems with 8 and 9 bins. Therefore, a total of seven bins are allocated for each individual cell.

The extant literature on gait recognition typically encompasses a range of 9 orientation bins, spanning from 0° to 180°. Each bin is given a value of 20°. The range of angles spans from 0° to 180°, rather than from 0° to 360°. The term «unsigned gradients» is used to refer to gradients that are represented by the same numerical value for both the gradient and its negative counterpart. However, this research examines a set of 7 orientation bins spanning from −180° to 180°, with each bin given a range of 51.43°. In the context of this experiment, the distinction between the gradient and its negative is not disregarded, since they are treated as distinct numerical values. The reason for this is because the experiment was carried out using gradients that were both signed and unsigned. It has been empirically shown that the use of signed gradients yields superior results compared to unsigned gradients in the context of GGMI.

The K-Nearest Neighbors (KNN) algorithm is used as the classifier for gait recognition. This research employs a neighbor count of 1 and using the Euclidean distance measure. The CCR (Correct Classification Rate) is used to evaluate the efficacy of the gait recognition system on the designated testing dataset.

The present study focuses on conducting experiments using the CASIA dataset.

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Experiments on CASIA A dataset. Among the four sequences, three sequences are designated for training purposes, while one sequence is reserved for testing. Table 2 presents the experimental findings obtained from the analysis of the CASIA A dataset, together with a comparison to the results reported in previous studies. The findings of this research demonstrate that the inclusion of the suggested characteristics in the computing process leads to a significant enhancement in the effectiveness of the gait recognition approach, particularly for the 45° and 90° views. The findings indicate that the CCR (Correct Classification Rate) of this research is somewhat lower for the 0° view, since the frontal view provides comparatively less spatial and dynamic information compared to other variants of the view.

Table 2. **Experimental results on CASIA A dataset**

Approach	0°	45°	90°	Average
[41]	93.22%	94.28%	95.42%	94.31%
[42]	**96.27%**	97.42%	98.21%	97.30%
Proposed	95.32%	**98.69%**	**98.67%**	**97.56%**

Source: **compiled by the authors**

Experiments on CASIA B dataset. Features were retrieved from all 11 perspectives of the dataset, including a total of 124 people. Features are derived from six gait cycles for each subject, in relation to each subject's respective topic. Therefore, a total of 744 GGMI's per view are retrieved, which is obtained by multiplying 124 by 6. The accuracy of categorization is determined individually for each perspective. In the study, a total of six gait sequences were examined. The first four sequences were designated for the purpose of training, while the final two sequences were set aside specifically for testing.

The findings for regular walking from various perspectives are shown in Table 3.

The new strategy is also evaluated and compared with current techniques in the literature from different perspectives. Table 3 illustrates the similar phenomenon. The study conducted in paper [43] demonstrates superior performance compared to the approach suggested in three specific scenarios of normal walking situations, namely 0°, 18°, and 180°. The suggested approach demonstrates superior performance across a majority of viewpoints, with the exception of the frontal view. Hence, changes in perspective result in corresponding modifications to visual attributes, including form and motion-related data.

CONCLUSIONS

To maintain the distinctiveness of GEI while eliminating extraneous details that may be considered less relevant, a transformation is used to turn GEI into GGMI. GGMI only encompasses the essential structural components of GEI. This paper introduces a novel feature vector that combines the Histogram of Oriented Gradients (HOG) with the sum variance Haralick texture descriptor. The aforementioned feature vector demonstrates enhanced reliability and effectively captures the spatial fluctuations inherent in gait. The dimensionality of the feature vector is decreased from 3780×1 to 63×1, resulting in a reduction in the computational complexity of the gait recognition system.

Experiments conducted on CASIA A and CASIA B dataset showed that the proposed approach performs better than other HOG-based methods except in the frontal image situation.

Table 3. **Experimental results on CASIA B dataset**

Approach	0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°
[43]	99.40%	**99.70%**	97.50%	97.24%	97.26%	97.71%	95.52%	96.60%	96.21%	98.52%	**99.65%**
[44]	91.16%	91.21%	92.42%	95.21%	95.74%	95.52%	94.23%	95.70%	94.67%	94.33%	94.42%
[45]	**100%**	98.60%	95.66%	94.45%	93.21%	93.72%	93.76%	95.32%	94.81%	97.46%	98.82%
Proposed	99.2%	99.1%	**98.24%**	**99.57%**	**99.21%**	**99.1%**	**98.60%**	**99.40%**	**99.1%**	**98.72%**	98.14%

Source: **compiled by the authors**

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Моделі та методи машинного навчання для розпізнавання людської ходи

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АНОТАЦІЯ

У цій статті розглядається проблема ідентифікації людини за допомогою розпізнавання ходи в системах біометричної ідентифікації. Крім того, були окреслені основні вимоги до біометричних характеристик людини, обговорені основні біометричні характеристики та їх застосування в системах біометричної ідентифікації. Також була досліджена можливість використання ходи як біометричного ідентифікатора, підкреслені її переваги в тому, що вона не вимагає попереднього надання персональної біометричної інформації та спеціалізованого обладнання. Потім був проведений аналіз наукової літератури в галузі розпізнавання ходи. В ході дослідження були визначені основні проблеми та виклики, з якими стикаються дослідники в цій галузі, а також домінуючі тенденції в розпізнаванні ходи людини в системах біометричної ідентифікації. Крім того, в цій статті запропоновано метод ідентифікації людини за ходою на основі гістограми орієнтованих градієнтів та текстурних ознак Гаралика. Вхідне відео перетворюється на серію фотографій, на яких зображено силует ходи. GEI створюється шляхом комбінування цих силуетів ходи протягом циклу ходи. Потім GEI перетворюється на зображення величини градієнта ходи (GGMI). Другим кроком є отримання рекомендованих характеристик ходи з GGMI учасників, які включені в даний набір даних. По-третє, для попередньої обробки отриманих характеристик використовується аналіз головних компонент (Principal Component Analysis, PCA). Це відбувається шляхом зменшення розмірностей, які негативно впливають на надійність класифікації, що, в свою чергу, призводить до покращення продуктивності. На останньому кроці класифікатор KNN використовується для присвоєння категорій характеристикам, які були зібрані з певного набору даних.Запропонований новий вектор ознак пропонує підвищену надійність та ефективно фіксує просторові варіації, присутні в патернах ходи. Важливо, що це зменшує розмірність вектору ознак з 3780×1 до 63×1, що призводить до зменшення обчислювальної складності системи розпізнавання ходи. Експериментальні тести, проведені на наборах даних CASIA A та CASIA B, демонструють, що запропонований підхід перевершує інші методи на основі HOG у більшості сценаріїв, за винятком ситуацій з фронтальними зображеннями.

Ключові слова: розпізнавання ходи; гістограма орієнтованих градієнтів; текстурні ознаки гараліка; аналіз головних компонент; класифікація; патерни ходи; комп'ютерний зір

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