

MODELS AND METHODS FOR GAIT-BASED PERSON IDENTIFICATION WHILE WEARING DIFFERENT OUTFIT

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Abstract. *This study presents a potential methodology for the identification of individuals based on their gait patterns, even when they are wearing different attire. The approach described in this study utilizes modified local patterns that have been specifically designed to be robust to rotation. These patterns enable the extraction of more discerning characteristics, particularly in scenarios where individuals may be wearing diverse clothing. The procedure was outlined in a comprehensive manner, including explanations for each step of the process. The experiments provided confirmation of the notable efficiency of gait-based person identification in scenarios where individuals wear varying attire.*

Keywords: *Surveillance systems, Human identification, Silhouette extraction, Gait Energy Image, classification, Local Binary Pattern, Gait recognition.*

Introduction

Abraham Maslow's research indicates that security is among the most fundamental and essential human requirements. Individuals consistently make an effort to safeguard themselves, fortify their residences against potential intruders, and defend their possessions against larceny [1].

The advent of contemporary video surveillance systems has facilitated the comprehensive recording of all activities transpiring within a designated region, enabling subsequent analysis of the acquired data. The utilization of video recordings enables the surveillance of individuals' movements, identification of individuals captured on camera, detection of unauthorized intrusion into private areas, and regulation of access to restricted zones [2].

The issue of face recognition in video has gained significant relevance in recent times. Among the various criteria that can be used to determine the identity of an individual in a video, facial features provide the highest degree of accuracy.

Nevertheless, the current state of recognition technology is unsatisfactory, and the dependability of these systems is restricted to the cooperation mode, which involves comparing an individual's face to a high-quality passport photograph. Faces may be obscured or inadequately visible in real-life scenarios, particularly during criminal investigations, for a variety of reasons including inadequate illumination, hoods, or uniforms. In such circumstances, identification requires additional characteristics, including gait [3].

According to biometric and physiological research, the gait of each individual is distinct and unfeasible, establishing it as a unique identifier analogous to fingerprints or irises [4].

One significant benefit of gait analysis is its capacity for remote observation; it does not necessitate high video resolution and, above all, does not demand subject interaction; the individual being recorded may be unaware that they are being monitored.

However, the issue of gait recognition is complicated by a variety of visual factors that influence gait, including footwear, objects in the hand, apparel, masks, and various camera settings and angles.

Hence, gait identification continues to exhibit inferior quality and dependability in comparison to face identification. Notwithstanding the advancements achieved with contemporary computer vision techniques, this dilemma remains solvable [5].

The applicability of numerous established methods is restricted to the specific conditions under which they were developed, thereby impeding their implementation in real-world settings.

Variations in apparel are among the most significant factors affecting the performance of human gait recognition algorithms [6]. It is self-evident that various garments can obscure portions of the human physique, resulting in a substantial alteration of the human silhouette and a deprivation of gait characteristics.

In the course of developing human locomotion identification systems, it is pertinent to develop a method of human identification that is independent of variations in human attire.

Thus, the purpose of this study is to devise and investigate a technique for identifying an individual based on their gait when they are attired in various articles of clothing.

1. Proposed method overview

The methodology being suggested is founded upon the GEI (Gait Energy Image) texture descriptor [7]. The utilization of region-specific distinctive characteristics in GEI enhances the efficiency of gait recognition. The methodological framework is illustrated in Figure 1.

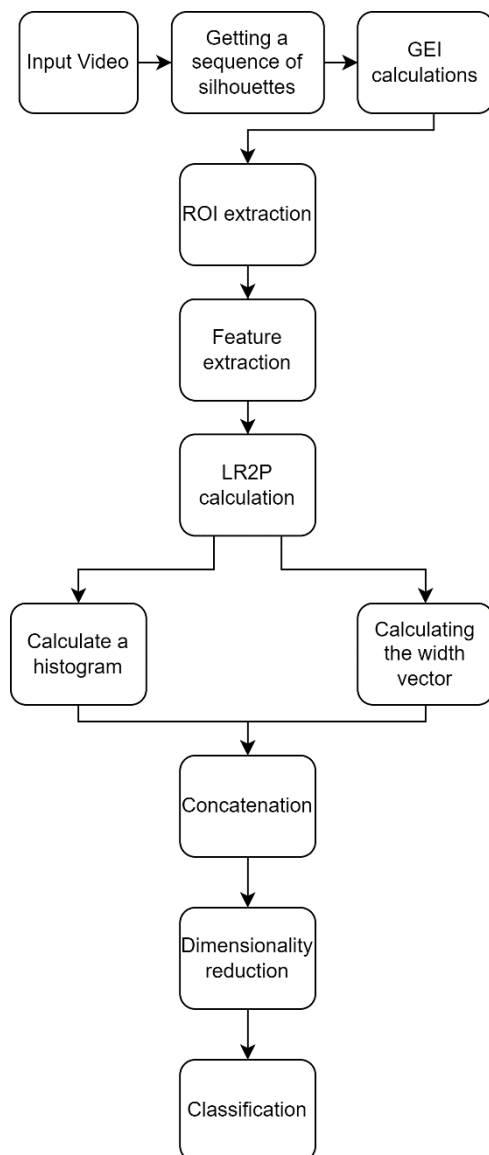


Fig. 1. Proposed method scheme

An initial step involves converting the gait video into an image sequence. Through processing, a silhouette is produced from these images. By subsequently integrating the silhouette images throughout the gait cycle, the GEI is generated.

Ahead of time, two regions of interest that are deemed less susceptible to apparel variations are chosen. From these two areas, features are extracted. Figure 2 illustrates an example of an image comprising the two extracted regions.

For feature extraction from the regions of interest, the LR2P (Local Rotation Robust Pattern) descriptor is utilized.

Due to the inclusion of a collection of gait images, GEI data contains a multitude of texture features. The texture features of this image are extracted utilizing LR2P. Furthermore, the LR2P descriptor pixel values are assigned to a histogram and a width vector.

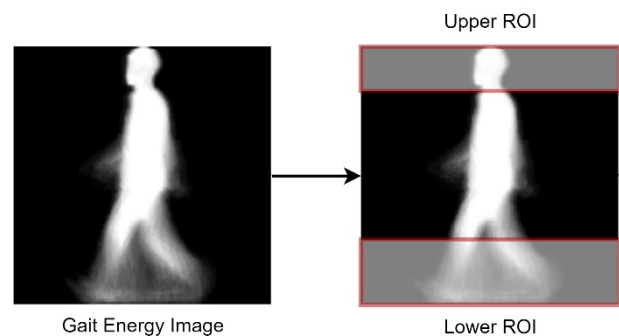


Fig. 2. Depiction of regions of interest

Therefore, the feature vector of each GEI is represented by the histogram and the width vector of the LR2P descriptor. The following algorithm illustrates the process of extracting locomotion features:

- 1: **Input:** Person GEI $GEI(x, y)$, size $k \times n$;
- 2: **Output:** Feature vector f ;
- 3: Begin;
- 4: Reading an image;
- 5: Extracting regions of interest: $GEI_1(x, y)$ and $GEI_2(x, y)$;
- 6: Calculating the LR2P descriptor;
- 7: Calculating histograms fh_i for two regions of interest;
- 8: Calculation of the width vector fv_i for two regions of interest;
- 9: Generating a fused feature vector $f = \{fh_1, fh_2, fv_1, fv_2\}$;
- 10: End.

Following this, the most irrelevant features are eliminated to reduce the dimensionality of the feature vector.

A classifier is subsequently employed to categorize the features, enabling the identification of individuals based on their gait.

2. Computing GEI (Gait Energy Image)

The Gait Energy Image (GEI) is the most prevalent profile of gait [7]. This image represents the average binary silhouette mask of an individual in motion for a single gait cycle. Assuming periodic repetition of body movements during walking, this spatiotemporal description of an individual's gait is computed. The resulting images depict the frequency with which a person in motion remains in a particular position.

This methodology is extensively employed, and numerous other techniques for gait recognition have been built upon its foundation.

Furthermore, numerous methodologies that do not exclusively rely on gait energy images entail comparable aggregations of additional fundamental characteristics.

For instance, the entropy of each pixel is computed for Gait Entropy Image (GENI) [8] rather than averaging the silhouette, and Frame Difference Energy Image (FDEI) [9] reflects the differences between silhouettes in consecutive frames of video. Illustrations of the gait energy images and binary silhouette mask are presented in Figure 3.

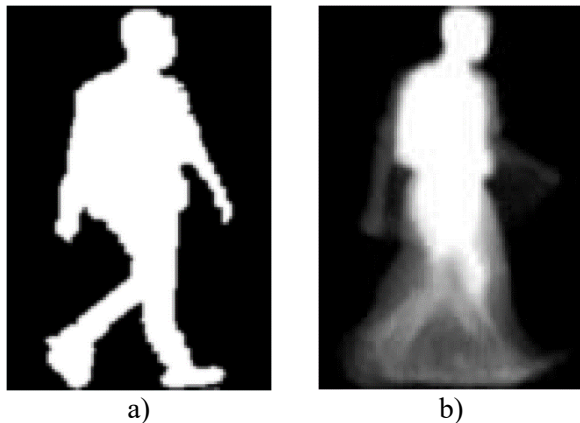


Fig. 3. – Examples of gait descriptors: a) – Binary silhouette; b) – Gait Energy Image

GEI remains the only method of gait representation that is currently being utilized and improved upon, notwithstanding the proliferation of such techniques. GEI can be employed to compute additional features, including histograms of oriented gradients (HOG-descriptors) [10] or histograms of optical flow (HOF-descriptors) [11], in a manner analogous to traditional black-and-white images. Additionally, it can be utilized to construct more intricate classification algorithms that exploit the unique characteristics of the gait recognition task.

As already mentioned, to calculate GEI, pre-processed silhouettes are averaged over a gait cycle as follows:

$$GEI(k) = \frac{1}{n} \sum_{t=1}^n I(t), \quad (1)$$

where n – is the number of frames in the k -th gait cycle, I – the normalized silhouettes.

3. Calculation of LR2P (Local Rotation Robust Pattern)

Local binary descriptors (LBDs) serve as efficient encoders of recurring local patterns, facilitating discrimination in numerous visual recognition methodologies. Recent years have witnessed the emergence of numerous variations of these descriptors due to their widespread usage.

In this paper, a nonlinear combination of the Local Binary Pattern (LBP) [12] and the Local Directional Pattern (LDP) [13] is introduced as the Local Rotation Robust Pattern (LR2P).

One drawback associated with these two descriptors is their failure to ensure rotation invariance. The LR2P simultaneously mitigates this limitation of these descriptors and maintains their individual stability.

Denote a pixel of the *Image* (x_p, y_p) with the intensity i_p . Denote as i_n , where $n = 0, 1, 2, \dots, 7$, the intensity of the 3×3 neighborhood surrounding pixel (x_p, y_p) , while disregarding the center of i_p . The orientation of the eight adjacent pixels is determined by the eight Robinson operator masks [14].

The intensity change magnitude in various directions for eight adjacent pixels is quantified using eight Robinson masks that are oriented in the direction of the aforementioned pixels.

Denoted as m_n , it represents the eight responses of the Robinson mask and corresponds to the pixels with intensities i_n ($n = 0, 1, 2, \dots, 7$). Assigning an exponent w_n ($n = 0, 1, 2, \dots, 7$) to each of these pixels is contingent on the rank of m_n among the eight outputs of the Robinson mask.

The local binary pattern is calculated using the following formula:

$$LBP(x_p, y_p) = \sum_{n=0}^7 s(m_n - i_p), \quad (2)$$

where i_p – *Image* intensity in pixel (x_p, y_p) , m_n ($n = 0, 1, 2, \dots, 7$) – 8 Robinson mask reviews, $s(x)$ – function, where $x = m_n - i_p$, is calculated using the formula:

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

The LR2P value for a pixel is calculated using the formula:

$$LR2P(x_p, y_p) = \sum_{n=0}^7 s(m_n - i_p) \cdot 2^{wn}. \quad (4)$$

Each adjacent pixel's binarization weight is equal to the value of the Robinson output potential directed in the direction of that pixel. The probability of an edge occurring in a specific direction is denoted by the output of the Robinson mask in that direction.

One notable benefit of utilizing the LR2P descriptor is that, subsequent to applying the LDP rule with the Robinson mask, the pixel value in the 3×3 neighborhood of a pixel (x_p, y_p) becomes the additive value of the pixel value's inverse in the opposite direction. The reason for this is the Robinson mask effect. As a consequence, exactly half of the pixel values within the 3×3 region consistently exhibit negative values, specifically those below the pixel intensity value (x_p, y_p) . In order to determine the LR2P value of a pixel, the remaining half of the pixels in its 3×3 vicinity is utilized.

As a result, the LR2P descriptor values obtained are remarkably comparable. Many descriptor values will therefore be equal to zero during the histogram construction phase for this descriptor; these can be omitted. As a result, the LR2P descriptor attains optimal recognition accuracy while utilizing a reduced number of features.

4. Obtaining a histogram of the LR2P and a width vector

Histogram generation of descriptors, including LBP and LDP, is a routine process in the majority of human recognition systems [15].

A histogram of LR2P values corresponding to each pixel in the image serves as the image descriptor in this instance. By utilizing the object's GEI, this

process attempts to extract distinguishing characteristics.

Due to the grayscale nature of GEI, the histogram representing the region of interest comprises 256 values. A 256×1 feature vector is thus acquired for a specific region.

Figure 4 illustrates a numerical calculation example of the width vector.

The grayscale implementation of the LR2P descriptor enables a more effective depiction of the GEI texture.

In this instance, the width along the horizontal axis of the LR2P descriptor image is utilized as a feature vector for recognition.

In order to determine the width vector fv_i , the count per row of texture pixels present in each row of the region of interest is maintained.

Three benefits accompany the proposed method for feature extraction.

Thirdly, the dimensionality of the feature space is drastically reduced. The initial benefit is that the method eliminates inert redundant information. Secondly, the vector is comprised of meaningful data.

Denote a region of interest GEI_i with a size $m \times n$. Let R_1, R_2, \dots, R_m denote the rows of the GEI_i array:

$$GEI_i = \begin{bmatrix} GEI_{11} & GEI_{12} & \dots & GEI_{1n} \\ GEI_{21} & GEI_{22} & \dots & GEI_{2n} \\ \dots & \dots & \dots & \dots \\ GEI_{m1} & GEI_{m2} & \dots & GEI_{mn} \end{bmatrix}. \quad (5)$$

Denote the k -th row of GEI_i as R_k . Then $R_k = [GEI_{k1} \ GEI_{k2} \ \dots \ GEI_{kn}]$.

Using the following formula, the pixel value at position GEI_{kj} (where $j = (1, 2, \dots, n)$) is determined:

$$GEI_{kj} = \begin{cases} 1, & \text{if } GEI_{kj} < 255 \\ 0, & \text{otherwise} \end{cases}. \quad (6)$$

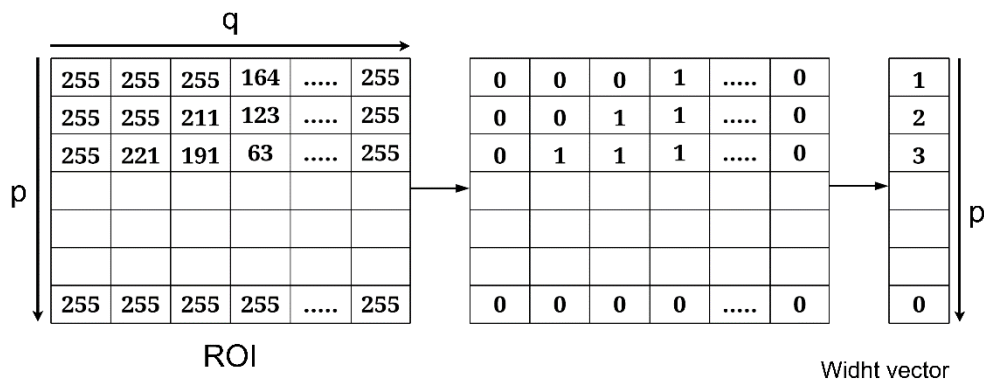


Fig.4. An example of calculating a width vector

Each pixel in the LR2P descriptor has a value between 0 and 255. The pixel value 255 is omitted

from the image due to its representation of the white background.

The calculation for the width vector of row R_k is as follows:

$$R_k = \sum_{j=1}^n GEI_{kj}. \quad (7)$$

5. Experimental study of the proposed method

In order to assess the effectiveness of the suggested approach, we employed two gait datasets OUISIR B and CASIA B comprised of subjects donning diverse fashion choices.

The B OUISIR dataset. The training set for the initial experiment conducted on the OUISIR B dataset comprises 68 subjects. Training requires one article of apparel (dress blouse, ordinary trousers), while the remaining articles are utilized for testing purposes. The assessment set comprises an assortment of garment combinations, excluding those that were utilized during the training phase.

It is particularly difficult to identify an individual wearing various designs of apparel when training was conducted using a singular set of garments.

The proposed procedure yields favorable outcomes when applied to various garment ensembles. The classification accuracy that was achieved, along with a comparison to frequently employed methods in the literature, is presented in Table 1.

The experimental findings validate that the suggested methodology enhances the precision of recognition irrespective of the various conditions of apparel. It illustrates the maintenance of feature invariance through the reduction of intra-class disparities among individuals' clothing ensembles.

Table 1

Method	CCR
Particle-based [16]	66.25%
Sliding window [17]	73.21%
Grid Segmentation [18]	81.57%
MLP [19]	80.58%
GEINet [20]	80.42%
Deep-CNN [21]	85.82%
Proposed	86.12%

In the second experiment, the OUISIR B dataset was utilized to construct a unified training dataset comprising locomotion patterns for 32 distinct clothing designs.

There are 2176 images in the training set, one sequence for each of the 68 individual subjects.

The remaining one sequence per of the sixty-eight subjects in each experiment is comprised of the test set.

Based on the outcomes of thirty-two experiments, it can be concluded that the proposed method effectively mitigates the issue of clothing variations and prevents a decrease in the recognition rate, irrespective of the magnitude of these changes (e.g., a long coat or a tiny cap).

The recognition accuracy varied between 85.50% and 98.50% for various categories of clothing (short trousers, short-sleeved shirt; baggy pants, short-sleeved shirt).

Obtained 92.02% is the mean CCR (Correct Classification Rate) value derived from all 32 experiments.

Dataset CASIA B. Table 2 displays the outcomes of the experiments, along with a comparison to previously documented methodologies.

Table 2

Method	0 °	18 °	36 °	54 °	72 °	90 °	108 °	126 °	144 °	162 °	180 °
[22]	67.17	56.19	80.05	71.15	75.09	77.18	75.05	65.12	64.42	64.56	66.12
[23]	80.42	84.32	85.17	87.66	91.34	91.35	87.83	86.29	87.42	84.88	83.04
[20]	75.12	77.21	74.12	78.52	81.82	82.81	81.65	76.71	80.02	82.11	80.52
[24]	97.18	99.49	97.46	94.18	88.36	90.24	89.42	94.21	92.75	91.25	93.92
[25]	97.92	98.72	98.05	95.12	92.60	92.75	91.50	93.17	92.68	92.94	94.41
Proposed	98.82	95.60	96.20	91.85	93.98	95.19	94.57	95.38	90.35	92.89	95.09

Each participant in the initial study utilizing the CASIA B gait dataset performed two garment change sequences (*cl*) and six normal gait sequences (*nm*).

For training purposes, the initial four sequences of normal locomotion (*nm*) were utilized. Clothing variations were evaluated utilizing the two *cl* sequences.

In most cases, the proposed method achieves superior results to those of other recognition methods evaluated on the CASIA B gait dataset.

As evidenced by results previously published in the field, the inclusion of various garments results in a diminished CCR value, rendering clothing a covariate characteristic that is primarily demanding.

They induce substantial alterations in the architectural forms of objects. The limited temporal and spatial variation in silhouettes throughout the locomotion cycle is a critical factor that detrimentally impacts the performance of recognition methods that rely on patterns. Enhanced feature discrimination is achievable through the application of a LR2P descriptor.

A second experiment was conducted using the CASIA B dataset with the purpose of determining whether or not the suggested strategy is successful under a variety of clothing situations from a variety of perspectives.

Experiments were carried out for each of the eleven various views that were included in the CASIA B gait dataset, which included sequences of 124 participants as a whole.

For every perspective, there were two separate trials carried out. Several different types of apparel were used to construct a single training dataset that included gait patterns.

496 patterns were included in the training set, which was comprised of four sequences: three *nm*-sequences and one *cl*-sequence.

In the first trial, the test set was comprised of three *nm*-sequences that were performed while wearing regular clothing.

Under a variety of clothing settings, the second experiment consisted of selecting one *cl*-sequence to serve as the test set.

This dataset was used to run twenty-two experiments that were built specifically for it.

In spite of the fact that the suggested technique is not intended to get around the issue of viewing angle, its performance is nonetheless evaluated based on different viewing angle configurations.

The findings of the experiments demonstrated that the suggested approach for feature extraction produced encouraging outcomes when applied to a variety of clothing variants when seen from a variety of perspectives.

Conclusions

This paper presents a novel approach to gait-based person recognition that is impervious to apparel

alterations and enables the achievement of high rates of recognition accuracy even when the subject is attired in various types of attire.

Utilizing the proposed LR2P descriptor, which is resistant to rotation and enables the acquisition of more discriminative features when the subject is attired in various types of apparel, forms the foundation of the proposed method.

An experimental investigation was undertaken to validate the efficacy of the devised method using the OUISIR B and CASIA B datasets. Each dataset underwent two separate experiments. It was determined that the proposed procedure can produce accurate results for various sets of garments on the OUISIR B dataset (86.12% accuracy rate). Even when these variations are substantial, the second experiment conducted on this dataset demonstrated that the proposed method can mitigate the issue of clothing variations without causing a decrease in the recognition rate. The mean accuracy of recognition achieved across all 32 experiments was 92.02%.

The experimental results obtained from the CASIA B dataset indicate that, in the majority of instances, the proposed method outperforms alternative recognition methods that were evaluated on the CASIA B gait dataset.

The second experiment, which was carried out using the CASIA B dataset, revealed the viability of the suggested feature extraction approach when it was applied to a variety of different versions of clothing that were observed from a variety of other viewpoints.

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MODELS AND METHODS FOR GAIT-BASED PERSON IDENTIFICATION WHILE WEARING DIFFERENT OUTFIT**Sergiy Purish¹, Thorsten Schöler²**¹*Odessa National Polytechnic University*, ²*Augsburg Technical University of Applied Sciences*

Abstract. The purpose of this study is to present a technique for detecting a person based on their gait. This approach is designed to be resistant to changes in clothing and to provide high identification accuracy rates even when subjects wear various kinds of apparel. Specifically, the technique is based on the exploitation of the suggested LR2P descriptor, which demonstrates resilience to rotation and allows the extraction of more discriminative characteristics, particularly when participants wear a variety of apparel. The OUISIR B and CASIA B datasets were used in an experimental investigation that was carried out in order to verify the efficiency of the approach that was specifically devised. For every dataset, there were two separate experiments that were made. It was discovered that the suggested technique achieved an accuracy rate of 86.12% when applied to the OUISIR B dataset, which resulted in beneficial outcomes for a variety of clothing sets. Furthermore, the second experiment conducted on this dataset indicated that the suggested strategy efficiently mitigates the problem of differences in clothing and maintains a high identification rate, even when such changes are large. This was proved throughout the results of the trial. There were 32 different tests, and the average recognition accuracy that was attained was 92.02% each. The experiment that was carried out on the CASIA B dataset demonstrated that, when compared to the outcomes of various other recognition techniques that were evaluated on the CASIA B gait dataset, the suggested approach outperformed them in the majority of situations. In addition, the second experiment, which was conducted on the CASIA B dataset, demonstrated the promising outcomes of the suggested feature extraction approach.

Keywords: Surveillance systems, Human identification, Silhouette extraction, Gait Energy Image, classification, Local Binary Pattern, Gait recognition.

МОДЕЛІ ТА МЕТОДИ ІДЕНТИФІКАЦІЇ ЛЮДИНИ ЗА ХОДОЮ В РІЗНОМУ ОДЯЗІ**Сергій Пуріш¹, Торстен Шолер²**¹*Національний університет «Одеська політехніка»*, ²*Аугсбурзький технічний університет прикладних наук*

Анотація. Мета цього дослідження – представити методику ідентифікації людини на основі її ходи. Цей підхід розроблений таким чином, щоб бути стійким до змін в одязі та забезпечувати високу точність ідентифікації навіть тоді, коли суб'єкти носять різні види одягу. Зокрема, методика базується на використанні запропонованого дескриптора LR2P, який демонструє стійкість до обертання і дозволяє виділити більше дискримінаційних характеристик, особливо коли учасники носять різноманітний одяг. Набори даних OUISIR B і CASIA B були використані в експериментальному дослідженні, яке проводилося з метою перевірки ефективності спеціально розробленого підходу. Для кожного набору даних було проведено два окремих експерименти. Було виявлено, що запропонована методика досягла точності 86,12% при застосуванні до набору даних OUISIR B, що призвело до позитивних результатів для різних наборів одягу. Крім того, другий експеримент, проведений на цьому наборі даних, показав, що запропонована стратегія ефективно пом'якшує проблему відмінностей в одязі і підтримує високий рівень ідентифікації, навіть коли такі зміни є значними. Це було підтверджено всіма результатами випробування. Було проведено 32 різних тести, і середня точність розпізнавання, яка була досягнута, становила 92,02% у кожному з них. Експеримент, проведений на наборі даних CASIA B, продемонстрував, що порівняно з результатами інших методів розпізнавання, які були оцінені на наборі даних ходи CASIA B, запропонований підхід перевершив їх у більшості ситуацій. Крім того, другий експеримент, проведений на базі даних CASIA B, продемонстрував багатообіцяючі результати запропонованого підходу до вилучення ознак.

Ключові слова: Системи спостереження, Ідентифікація людини, Виділення силуету, Енергетичне зображення ходи, Класифікація, Локальний бінарний шаблон, Розпізнавання ходи.

Отримано 27.09.2023



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