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Adaptive Parts Selection for Part-based Gait Identification Using Legendre and Zernike Moments Considering Clothing and Carrying Conditions

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ABSTRACT
Human gait analysis has gained significant traction as a non-intrusive biometric in surveillance systems, with many new approaches introduced. However, environmental or external variables—known as covariates—frequently compromise recognition accuracy. A major hurdle is isolating specific body parts that remain effective parts despite these cofactors. To address this, we introduce a novel method that employs Legendre and Zernike moment-based thresholds to isolate the most critical gait features. By adaptively matching probe data to the gallery set, our approach focuses only on the most resilient gait components. Experimental results demonstrate that this targeted selection technique significantly outperforms existing methods, particularly when subjects change their clothing or carry various objects.
Keywords — Human gait, Legendre moment, Zernike moment, Effective parts, Gait identification, Clothing and carrying conditions.

I. INTRODUCTION

Human gait is regarded as one of the few biometric features that can be captured remotely without cooperation and physical contact of a subject. Other biometric features such as handwriting, signature, fingerprint, face, voice and iris are also measured which recognizes an individual in very close contact or cooperation. Gait recognition has gained tremendous attention over the last few decades due to its strength in (i) obtaining gait data at low image resolution at a distance from camera, (ii) gait is difficult to hide and (iii) gait as unconscious behaviour and can be captured in real-time [1]. However, gait can be sensitive to surface type, clothing, carried items, and clutter or occlusions in the scene. These represent the challenges of tackling the gait identification task to learn unique and invariant features from the human gait [2].

Gait recognition approaches are found into two broad categories: (i) Model-based and (ii) Model-free techniques.

The model-based approaches use strong prior knowledge for human gait extraction. More specifically, those methods extract the gait features such as structures and motions by setting the human model to image sequences. In [3], an articulated model is used to extract joint angles as features for matching. In [4] kinematics of leg motion is extracted as a gait feature on the basis of Fourier analysis. In [5] static shape parameters and gait period are extracted through the use of articulated body model. These methods efficiency in terms of time complexity is very limited due to complex matching and time-consuming searching. On the other hand, model fitting fault is another challenge of this method. In fact, having a high-quality model is almost impossible without high quality image sequences [5].

On the other hand, model free methods do not use structural and human motion models [6]-[10]. Instead, they operate on a video sequence. Such methods either generate a prototype image or use the time-based information of human motion [11]-[16] such as position, shape, velocity, colour and texture from the sequence of silhouettes. Model-free methods [6], [17] are more robust to noise, computationally efficient, comparatively insensitive to the quality of gait silhouettes and have a comparable or better performance compared with the model-based approaches. However, variations in different cofactors alter an individual's appearance, making the model-free gait identification task much more difficult.
The recognition performance can be improved by representing the gait with most discriminating features and discard the affecting features that contaminated with different cofactors.

In this work human body parts are defined experimentally [9]. The effective parts are selected adaptively and independently for a given probe to gallery using Legendre and Zernike moment-based threshold for the purpose of gait recognition. Having obtained different number of body parts, GEI, GEnI, DFT and EnDFT [9] representation is computed and exploited as gait features.

For clothing and carrying conditions, most area of the static parts are covered and altered. So, to give emphasis on dynamic parts entropy and frequency-based features are used for recognition and shows improved result.

The outline of this paper is as follows. The related works is introduced in section II. In section III, different human gait representation techniques are described. Thereafter, human body parts definition and selection procedure is addressed in section IV. Experiments in section V, results and discussion is presented in section VI. Finally, concluding remarks and future plans are given in section VII.

II. RELATED WORKS

Model-free procedures [6, 17] consider gait features as a sequence of silhouette to represent gait for measuring the similarity. In [18], direct silhouette sequence matching as a baseline method is proposed. A new spatiotemporal pattern that represents gait shape variation information is used in [19] as a gait feature. The feature is obtained by projecting pixel values of difference frames along horizontal or vertical axes in exactly the same way as the original frieze pattern method in [20]. Cuntoor et al. [21] systematically analyzed different components of human gait by investigating dynamic and static body components. The left and right projection vectors are constructed to study the motion of the hands and legs, and width vector for leg dynamics within a gait cycle. Self-similarity plots were used for gait recognition in [22]. Computing average of silhouettes is proposed in [23] for gait recognition. In [24], average is computed on the silhouette value pixel-by-pixel over the gait period and proposed the most prevailing baseline algorithm. A gait entropy image (GEnI) [25] is generated by computing pixel-by-pixel entropy of the GEI. GEnI highlights the dynamic areas of human gait. A gait flow image (GFI) [26] is produced by using an optical flow field over binary silhouette sequences without considering any model. Discrete Fourier Transform (DFT) [27] is computed as pixel-by-pixel-by-frame amplitude spectra of zero-, one-, and two- times frequency elements, because it preserves and highlights the uncertainty of gait dynamic area.

Most of the proposed part-based approaches concentrate on a similarity measurement procedure to mitigate the clothing and carrying cofactors and speed changes. These methods focus to find out the most affected body parts that are heavily contaminated with different cofactors. In order to improve the performance most of the methods use unaffected parts and reject affected parts for recognition. One of the first methods that partition the human body into parts for gait identification is described in [28]. The parts are considered separately and used in both person identification and gender classification. In [29], a component-based gait recognition method is proposed considering unequal discrimination ability of each part. Fixed weights are measured for different components in the training phase. A part-based approach is proposed in [9] for clothing and carrying and speed changes cofactors. They utilized EnDFT gait representation for clothing and carrying condition for improved performance. The body is partitioned into less effective and more effective parts considering the effects of covariate factors. Hossain et al. proposed a method in [30] to segment the silhouette into eight sections with 4 overlaps on the basis of anatomical statistics [31]. In this method, higher weights are assigned to the unaffected body parts and lower weights to the affected body parts to reduce the effects of covariate factors. They adaptively measured the weights for different parts with clothing categorization. In [32], seven gait components are defined. The effectiveness of the components is observed both individually and in certain combinations for both gait recognition and gender classification. Both supervised and unsupervised feature selection methods are developed in [33] which validated using the CASIA B gait datasets and performance improved significantly.

III. HUMAN GAIT REPRESENTATIONS

Most of the feature-based gait recognition approaches exploit gait silhouettes to represent the gait feature. In the first step of finding gait silhouette volume (GSV) [27], background subtraction is performed on each frame of a given video sequence to obtain gait silhouettes. In the next step each background-subtracted gait silhouette is registered to obtain the spatio-temporal GSV. All the gait silhouettes are processed by applying size normalization into a fixed size of 128 × 88 pixel. This is followed by estimation of gait period done by estimation of the normalized autocorrelation of GSV [29]. In the following section some existing gait representation approaches are introduced.

A. Gait Energy Image (GEI)

The average of normalized silhouette images taken over a complete gait period is called GEI [23]. GEI contains higher intensity areas and lower intensity areas. In GEI, the higher intensity areas are labelled as static areas (head and body) and lower intensity areas are labelled as dynamic areas (swings of legs and arms). GEI is computed through the following equation

$$GEI(x,y) = \frac{1}{N}\sum_{n=1}^{N} B(x,y,n)$$

where, x and y are the pixel coordinate in the silhouette image B, n corresponds to the frame number in a gait period, N is the total number of frames per gait period. GEI are given in Fig. 1.

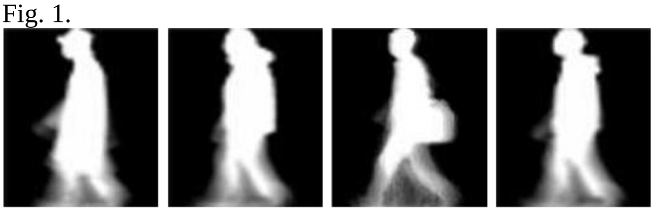

Fig. 1 Gait Energy Images of clothing and carrying conditions [9]

B. Gait Entropy Image (GEnI)

In GEI, static and dynamic areas are distinguished my measuring Shannon entropy at each pixel location. The intensity value of the silhouette at each pixel location is taken as a discrete random variable. Shannon entropy measures the uncertainty associated with the random variable over a complete gait period having N silhouettes through the following equation

$$GEnI = H(x,y) = -\sum_{k=1}^{K} P_k(x,y)\log_2 P_k(x,y)$$

where, x and y are the pixel coordinates in the GEI, $P_k(x,y)$ is the probability that the pixel belongs with respect to the kth value, $K=2$ since the silhouettes are binary images, $P_1(x,y) = \frac{1}{N}\sum_{n=1}^{N} B(x,y,n)$ (i.e. the GEI) and $P_0(x,y) = 1 - P_1(x,y)$, n corresponds to the frame number in a gait period and N is the total number of frames per gait period [6], [25]. Fig. 2 shows GEnI.

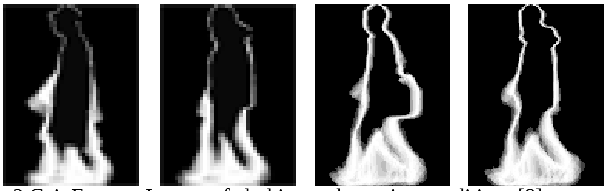

Fig. 2 Gait Entropy Images of clothing and carrying conditions [9]

C. Discrete Fourier Transform (DFT) Image

By applying DFT over the frames in a gait period, an amplitude spectrum of the GSV is calculated [27]. DFT and amplitude spectra is calculated through the following equation

$$G(x,y,k) = \sum_{n=0}^{N-1} B(x,y,n)exp^{-j\omega 0kn}$$

$$A(x,y,k) = \frac{1}{N}|G(x,y,k)|$$

where, x and y are the pixel coordinate in the silhouette image B, n corresponds to the frame number in a gait period, N is the total number of frames per gait period, $\omega 0$ is the base angular frequency for a gait period and k is the frequency component. First three frequency components are considered for DFT calculation and shown in Fig. 3. Other frequency components are discarded that representing noises. Among the three frequency components, first component is equivalent to GEI, second component represents the asymmetry of the left and right motion and the third component represent the symmetry.

Fig. 3 DFT images of clothing and carrying conditions [9]

D. Frequency-domain Gait Entropy Image (EnDFT) Image

Both GEI and DFT contains static (e.g., torso) and dynamic (e.g., leg, arms) components together. However, in [25] it is found that GEI and DFT are vulnerable in the variations of different cofactors. GEnI usually outperforms GEI. However, GEnI produces similar result to the DFT because the last two components of DFT represent the most dynamic nature of the gait. In this method, DFT based entropy gait features are extracted. The intensity value of the EnDFT is computed from the DFT by computing the entropy of DFT as GEnI.

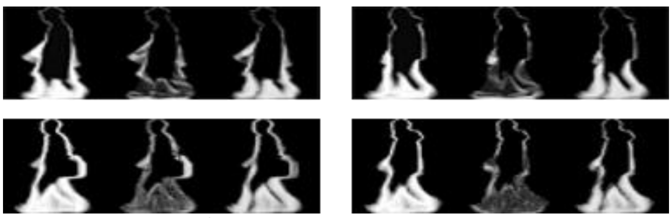

Fig. 4 EnDFT images of clothing and carrying conditions [9]

IV. GAIT PARTS DEFINITION AND SELECTION

This section is to define the parts of human gait automatically from a training data set depending the effectiveness of the covariate condition. The next step to select the most effective parts and discard the redundant part to overcome the difficulties arises in various cofactor conditions specifically for clothing and carrying conditions.

A. Gait Parts Definition

The whole human body is divided into very small segments each of which is considered as a single row for part definition [34]. We start from the bottom single row and measure rank -1 recognition rate. Then each immediate upper single row is merged to form sub-segments and calculated the recognition rate in each step until the top row is reached. The training subset of the OU-ISIR Gait Database, the Treadmill Dataset B is divided into gallery and probe subset for finding the recognition rate. Gallery subset contains only the standard clothing type and probe subset consists with other clothing types. Fig. 5 shows the effect of cumulative row-wise recognition rate.

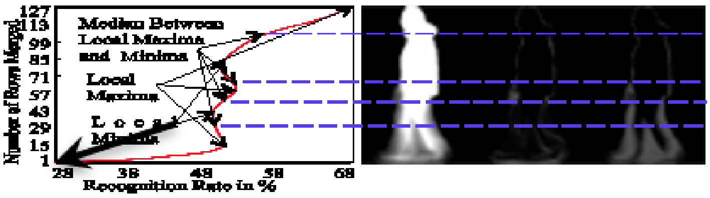

Fig. 5 Human gait parts definition and selection [9]

B. Adaptive Gait Parts Selection

In this research, Legendre moments and Zernike moments has been used for selecting effective human body parts adaptively in the presence of covariate conditions such as clothing and carrying and speed changes gait recognition. The whole procedure of effective parts selection is presented in Algorithm 1. Legendre moments and Zernike moments are invariant to geometric transformations. However, they are not invariant to the covariate conditions.

Legendre moments, were first introduced by Teague [35]. The Legendre moments used Legendre polynomials as its basis set. To compute Legendre moments from a digital image the coordinates of the image must be normalized into [-1, 1]. Therefore, the numerical approximate form of Legendre moments [36], for a discrete image of $M \times N$ pixels with image intensity function $f(x, y)$, is

$$L_{pq} = \lambda_{pq} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} P_p(x_i) P_q(y_j) f(x_i, y_j)$$

where, $\lambda_{pq} = \frac{(2p+1)(2q+1)}{M \times N}$, x_i and y_j denote the normalized pixel coordinates in the range of [-1, 1].

Zernike moments of an image are determined following three steps, computation of radial polynomials, computation of Zernike polynomials, and computation of Zernike moments.

These computations are carried out by projecting the image onto the Zernike polynomials.

To compute Zernike moments from a digital image the coordinates of the image which must be normalized into [0, 1] by a mapping transform. The discrete form of the Zernike moments on an image of size $M \times N$ is expressed as

$$Z_{pq} = \frac{p+1}{\lambda} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} R_{pq}(r_{xy})\, e^{-jq\theta_{xy}}\, f(x,y)$$

where, $0 \le r_{xy} \le 1$ and λ is a normalization factor. In the discrete implementation of Zernike moments, the normalization factor λ must be the number of pixels located in the unit circle by the mapping transformation and corresponds to the area of a unit circle π in the continuous domain. The transformed θ_{xy} phase and the distance r_{xy} at the pixel of coordinates (x, y) are given by

$$r_{xy} = \sqrt{\left(\frac{2x-(M-1)}{M-1}\right)^2 + \left(\frac{2y-(N-1)}{N-1}\right)^2}$$

$$\theta_{xy} = tan^{-1}\left(\frac{(2y-(N-1))/(N-1)}{(2x-(M-1))/(M-1)}\right)$$

Algorithm 1

1. A gallery consists of images is taken as input
2. Each image partitioning is carried out on the basis of part definition
3. Legendre moments or Zernike moments are computed for each part of all gallery images
4. Average of Legendre or Zernike moments are calculated for the same parts of the whole gallery found in step 3
5. Partition each image of probe sets according to the part definition
6. Compute Legendre moments or Zernike moments for each part of probe images
7. Find minimum of Legendre moments or Zernike moments for each part of images found in step 6
8. If the minimum Legendre moments or Zernike moments of a probe is less than or equal to the average value of gallery, set the weight of this part to 1. Otherwise set to 0.
9. The parts with weight 1 are used in probe gait recognition.

V. EXPERIMENTS

Let a probe sequence P with m subsequence's Pr $\{r = 1$ to $m\}$ and a gallery sequence G with n subsequence's G_s $\{s = 1$ to $n\}$. The matching measure for the subsequence's is simply chosen as the Euclidean distance between P_r and G_s (let $d^{sub}(P_r, G_s)$). First, we compute the minimum distances for each of the probe subsequence P_r to a gallery sequence G is defined with i^{th} body part as

$$d_i^{subs}(P_r, G) = {}^{min}_{\;r}[d_i^{subs}(P_r, G_s)]$$

Then, we compute the median of the minimum distances for each of the probe subsequence P_r as the distance between a probe P and a gallery G sequence is defined as

$$D_i(P, G) = {}^{median}_{\;\;r}[d_i^{subs}(P_r, G)]$$

In our part-based method, we summed each individual selected part's distance to get the final distance for k-NN based classifier as follows

$$D(P, G) = \sum_{i=1}^{N_{parts}} D_i(P, G)$$

The experiments carried out in this work to show the effectiveness of the effective and less effective body parts for human gait recognition using different gait representation. The details of the datasets used in this study are discussed in this section. The following two benchmarking gait datasets with most of the challenging cofactors are used in our experiment.

(i) The OU-ISIR Gait Database, the treadmill dataset B

(ii) The CASIA Gait Database, dataset B

The OU-ISIR Gait Database, the Treadmill Dataset B [36] is chosen due to its massive variation in clothing cofactors which is one of the most challenging artifacts. The dataset is a collection of 68 subjects with at most 32 combinations of different types of clothing such as skirt, raincoat, down jacket, long coat, hat, parker, muffler, short pants, casual wears, regular pants, half shirt, full shirt etc. This whole dataset is divided into three subsets: training set, gallery set and probe set. This training set holding 446 video sequences of 20 subjects (10 males and 10 females) with the range of 15 to 28 different clothing combinations are used for part definition in training phase. The training dataset is not used in validation phase. Other two subsets (gallery and probe) of OU-ISIR dataset B are used in testing phase. Gallery set contains only standard clothing type, i.e., regular pant and full shirt of 48 subjects. Probe set contains 856 sequences of these 48 subjects considering all types of different clothing combinations excluding the standard one.

The CASIA Gait Database, Dataset B is chosen due to its subject diversity with multiple sequences and multiple cofactors. The dataset contains normal walking sequences, carrying objects (i.e., carrying a bag) and only one clothing type (i.e., wear a bulky coat). The total 124 subjects contributed to the dataset. There are 10 walking sequences with the cofactors are captured from each of the subjects. This dataset is used only for validation of the proposed method.

VI. RESULTS AND DISCUSSION

Extensive experiments are carried out on CASIA B dataset and OU-ISIR dataset B on our defined partition system. We have selected body parts adaptively using Legendre and Zernike moments-based weight calculation.

TABLE I
COMPARATIVE RESULTS

Method	Part Selection Method	Dataset	CCR (%)
EnDFT+LDA (proposed)	Legendre	OUISIR B	**74.30**
DFT+LDA (proposed)	Legendre	OUISIR B	68.11
EnDFT+LDA (proposed)	Zernike	OUISIR B	**71.85**
GEI+LDA (proposed)	Legendre	CASIA B	**83.02**
DFT+LDA (proposed)	Legendre	CASIA B	**82.24**
GEI+LDA (proposed)	Zernike	CASIA B	**80.69**
DFT+LDA (proposed)	Zernike	CASIA B	**80.22**
Bashir et al. [7]	-	CASIA B	74.2
Rokanujjaman, M. [10]	Local maxima and minima	CASIA B	77.69
Part based EnDFT [10]	Local maxima and minima	OUISIR B	72.78
Baseline+GEI [23]		OUISIR B	55.26
PCA+LDA+GEI [24]		OUISIR B	54.32
PCA+LDA+GEnI [25]		OUISIR B	57.36
Part-based [30] Without weight		OUISIR B	58.06
Whole DFT [36]		OUISIR B	58.06
Maryam Bukhari et al. [37]	-	CASIA B	**90.32**
Hawas, A.R. [38]	-	CASIA B	64.1
Shiqi Yu et al. [39]	-	CASIA B	68.01
Jingran Su et al. [40]	-	CASIA B	75.03
Guoheng Huang et al. [41]	-	CASIA B	**81.50**
Gupta, S.K. [42]	-	CASIA B	73.8

The proposed methods are evaluated over two datasets under different covariate cofactors. Table I shows the results for the OUISIR B and CASIA B dataset. The results achieved by our method and most of the existing methods are outlined in Table 1. The comparison is carried out on the basis of different feature extraction methods and part selection methods. The method used in [42] performs better than our proposed method. However, the proposed method outperforms all the other compared methods achieving highest 83.02% recognition rate based on GEI+LDA and Legendre moments for CASIA B dataset and 82.24% recognition rate based on DFT+LDA and Legendre moments for the same dataset. In case of another dataset OUISIR B, best performance (74.30%) is obtained so far with respect to the performance of the other existing methods.

VII. CONCLUSIONS

In this research human body parts are defined experimentally and selected adaptively using Legendre and Zernike moments for the purpose of gait recognition. Having obtained different number of body parts, GEI, GEnI, DFT and EnDFT representation is computed and exploited as gait features. For speed changes the dynamic parts are responsible for intra-class variation and static parts are useful as an invariant feature. So, only the GEI representation is used for speed changes dataset because the other representation highlights the dynamic body parts and lessen the static parts. The proposed parts selection methods are compared with previously published methods. The recognition rates of our proposed methods confirm the effectiveness and validity over the four comprehensive benchmarking gait datasets under the clothing and carrying conditions and speed changes. The proposed methods perform better in most of the cases compared with the results of the other recognition methods verified on the OUISIR B and CASIA B gait dataset. In future, more covariate conditions like speed changes, occlusion etc, should be addressed for real time human gait identification.

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