Gait Recognition Performance Enhancement Using Dynamic Parts Selection

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Gait Recognition Performance Enhancement Using Dynamic Parts Selection

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Keywords

- Biometrics
- Human gait
- Person identification
- GEnI (Gait Entropy Image)
- Dynamic parts selection

ABSTRACT: Biometrics are widely used in person identification with the view to visual surveillance, monitoring applications as well as in medical applications. Among all other biometrics gait gained the researchers attention as it can identify a person uniquely without cooperation and it is impossible to conceal gait. The main advantage of gait biometrics is that, we can collect gait data from distance and don't need high level of information. In this paper we use gait entropy image to represent gait data that highlights dynamic features of gait. Then we divide the gait entropy image into eight parts including some overlapping parts. Finally, we select some parts dynamically to contribute in classification based on threshold value and discard some parts dynamically that decrease the gait recognition performance. In our work,we use OU-ISIR Treadmill dataset B, which is a large dataset including 68 subjects with 32 combinations of clothing types. After successfully completing the dynamic parts selection approach, we achieve the result that is better than some existing part based and whole gait recognition approach.

1. INTRODUCTION

Gait is used as a behavioral biometrictrait to solve human identification problemsby without human cooperation at distance[1,3,4]. Other biometrics traits such as fingerprint, handwriting, voice, iris, DNA,odor, hand geometry, ear shape, face and signature have been used toidentify a person with human cooperation at closer distance with high definition data.Human gait has gained the attention as it can solve the identification problems with lowregulation data[2] and solve the identification problem at distance.Nikolaos V et al. [5] and SudeepSarkar et al. [6] describe the most important gait covariates those affect gait. Clothing variation is the most sensitive covariate condition between the gallery and probe dataset.We propose Gait Entropy Image(GEnI) to highlight dynamic gait features as well as static features.GEnI is considered as robust regardless of appearance change with clothing variations. This feature collects the clothing invariant information with respect to changing appearance in silhouette shape.

The following major contributions are made in this research: (i)Neglecting subject cooperation, (ii) Proposed features representation using GEnI, which highlights dynamic features of human gait andinvariant regardless of clothing variations and (iii) Dynamic parts selection and weighted integration technique are used toimprove the gait identification performance.

2. RELATED WORK

Gait analysis and modeling approaches based on computer vision techniques can be divided in two categories: the model-free approaches[7, 8]and the model-based approaches. Many researchers used model-based approach to understand the gait features byestimating the static and dynamic body parameters [10, 2, 11]. Using baseline method Sarkar et al.[6] proposed a direct silhouette sequence matching. Lee et al. [9] proposed a technique to model the seven segments of human body. Wang and Suter [12] proposed locality preservation projections to present high quality silhouette images.Kusakunniran et al. [13] proposed regression based view transformation model, which was used to remove view variations.Boulgouris[25]proposed a component-based gait recognition that considers theunequal discrimination ability of each part. In [26, 27] seven gait components are defined. BirBhanu [14] proposedGait Energy Image (GEI). ShamsherSingh et al. [15] proved that using GEI the performance of gait recognition can be improved. Lin Chunli et al. [16] proposed Enhanced Gait Energy Image (EGEI) along with two dimensions PCA for classification.Khalid Bashir et al. [17] suggested a statistical learning theory based feature selection technique from Gait Energy Image. Sivapalan et al. [18] tried to overcome the appearance based problem of GEI by in using 3rd dimension approach named Gait Energy Volume. Researchers try to represent human gait with more dynamic feature named Gait Entropy Image(GEnI). Khalid Bashir et al. [7, 20] proposed GEnI to improve the results of person identification regarding clothing variations. Hossain et al.[22] proposed dividing human body into multiple parts with some overlapping parts and weighted integration technique. Md. Rokanujjaman et al. [21] proposedGEnI and dividing human body into multiple parts.Istiaque Ahmed et al. [23] proposed EnDFT (Frequency Domain Gait Entropy) and part based sequence combination technique.

3. GAIT DATA SET WITH CLOTHING VARIATION

In our work, we use OU-ISIR (Osaka University – Institute of Scientific and Industrial Research) treadmill dataset B.Yasushi Makihara et al. [24]described treadmill dataset B in details. Dataset B contains images of 68 subjects up to 32 combinations of clothing types. Within the 68 subjects 30 are males and 38 are females. Table 1 shows the clothing are used in OU-ISIR dataset B. The dataset contains three sets:

(i) Training set containing 446 sequences for 20 subjects with all types of clothes. It contains 10 males and 10 females.

(ii) Gallery set containing 48 sequences for remaining 48 from total 68 subjects with single type of clothes means standard clothes(Regular Pant(RP) and Full Shirt(FS))

(iii) Probe set containing 856 sequences for remaining 48 subjects with other types of clothes.

Table 1List of cloth used OU-ISIR treadmill dataset B

Abbreviation : Name	**Abbreviation : Name**	**Abbreviation : Name**
RP : Regular Pants	**HS :** Half Shirt	**CW :** Casual wear
BP : Baggy Pants	**FS :** Full Shirt	**RC :** Rain Coat
SP : Short Pants	**LC :** Long Coat	**Ht :** Hat
Sk : Skirt	**Pk :** Parker	**Cs :**Casquette Cap
CP : Casual Pants	**DJ :** Down Jacket	**Mf :** Muffler

Different clothing combination used in OU-ISIR treadmill dataset B as bellow.

Table 2Clothing combinations

#	S_1	S_2	S_3	#	S_1	S_2	#	S_1	S_2
2	RP	HS	–	A	RP	Pk	T	Sk	FS
3	RP	HS	Ht	B	RP	DJ	U	Sk	Pk
4	RP	HS	Cs	I	BP	HS	V	Sk	DJ
9	RP	FS	_	K	BP	FS	D	CP	HS
X	RP	FS	Ht	J	BP	LC	F	CP	FS
Y	RP	FS	Cs	L	BP	Pk	E	CP	LC
5	RP	LC	_	M	BP	DJ	G	CP	Pk
6	RP	LC	Mf	N	SP	HS	H	CP	DJ
7	RP	LC	Ht	Z	SP	FS	O	CP	CW
8	RP	LC	Cs	P	SP	Pk	R	RC	RC
C	RP	DJ	Mf	S	Sk	HS			

4.FEATURE SELECTION TECHNIQUE

Gait cycle is calculated as AnupNandy et al. [28] described in their paper. Gait period indicates therequirednumber offramesfor one complete gait cycle.The mathematical definition of entropy image also described in[28].Gait energy image(GEI) is an effective gait representation technique proposed by Han and Bhanu [14, 25]. GEI represents the static areas (head and body) as well as dynamic areas (swings of legs and arms) of the gait. If $B(x, y, n)$, are the pre-processed binary gait silhouette images at time $'n'$ in a sequence then GEI is defined as follows:

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

Where,$'N'$ is the number of frames in a gait cycle, $'n'$ is the frame number and $'x\,'$,$'y\,'$ are the values of 2D image coordinates.

Entropy is a measure of irregularity of states such as imbalance, uncertainty like dynamic areas of human gait as Bashir K et al. [7] described in their work for human gait identification using gait entropy image.If any source generates k symbols, then average self-information obtained from k number of output generated from that system is,

$$-k\sum_{j=1}^{j} \ p(a_j)\, log \quad p(a_j)$$

Where,a_j are symbols and $p(a_j)$ are source symbols probability. The average information per source output, i.e. entropy is:

$$H(Z) = -k\sum_{j=1}^{j} p(a_j)\, log \quad p(a_j) \ (2)$$

Fig.1 GEI(Gait Energy Image)

Fig.2 GEnI (Gait Entropy Image)

The entropy of this variable over each gait period can be computed as described in[7].

$$H(x, y) = -k\sum_{j=0}^{1} p_j(x, y) log_2 p_j\ (x, y)\ (3)$$

Gait Entropy Image (GEnI) is computed from GEI image using equation (3), Where,$p_1(x, y)$represents value from GEI and $p_0(x, y) = 1 - p_1(x, y)$, $GEnI$ contains the high value for dynamic areas and low value for comparatively static areas of human gait.

4. DIVIDING GAIT IMAGE INTO MULTIPLE PARTS AND DYNAMIC PART SELECTION APPROACH

Based on some anatomical properties Hossain et al.[22] divide the human body into eight parts. Following the process, we divide human body vertically for a body height *H*. First segment at neck(0.870H), second segment waist(0.535H), third segment pelvis(0.480) and the fourth segment is knee(0.285H) thus we get eight parts. Parts and corresponding covered areas are shown in Fig.3. Part-5, Part-6, Part-7 and Part-8 are overlapped to overcome the difficultiescreated by clothing variations.At each area k, we select sequences part dynamically of a probe if $d^k_{n,s}$ □ $\bar{d}^k_{min}$and the selected areas are marked with letter Yas shown in Fig.4. We consider those selected parts of a probe having high similarities with the gallery. Parts which don't satisfy the above condition are initially not selected and marked with letter N as shown in Fig.4. Here, the threshold $\bar{d}^k_{min}$ is computed from corresponding probe and gallery as follows :

$$\bar{d}^k_{min} = min_n \ (\bar{d}^k_n)(4)$$

$$\bar{d}^k_n = \frac{1}{S}\sum_{s=1}^{S} d^k_{n,s} \ (5)$$

Moreover, at each area in case that at least one sequence of a person is selected, then we consider that the matching scores of all sequences of the person are also high. This way, even if some of the sequences of a person are not selected(N), but others are selected(Y), we add those non-selected sequences into selected sequences asshown in Fig.4.

We determine the distance as matching weight of each area $d^k_{n,s}$between the features of the probe and those of all galleryas follows:

$$d^k_{n,s} = E_{dist}(I^k_{PRO}, I^k_{GAL,n,s})(6)$$

Where,$d^k_{n,s}$ is the Euclidian distance(E_{dist}) of a probe part 'k' to 'n' gallery's part k of sequence 's' ;I^k_{PRO} is the$k$ part of a probe of current sequence and $I^k_{GAL,n,s}$ is the corresponding k part those of a persons in the gallery. N is the number of people in the gallery as *1* □□ *n* □□ *N* .*S* is the number of sequences of each person(one sequence consists of images of one gait cycle) as $1 \le s \le S$of a person. K is the number of divided areas or parts as $1 \le k \le K$.

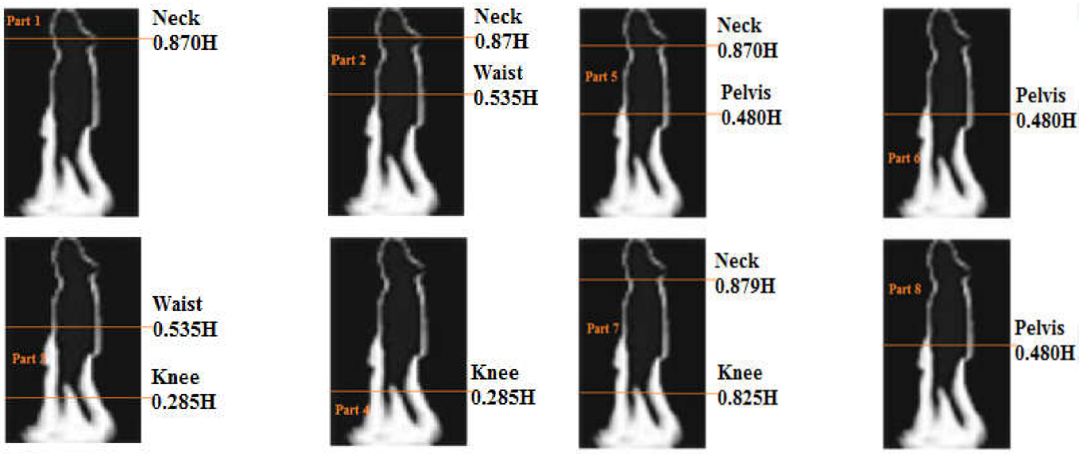

Fig.3Division the Gait Entropy Image into eight parts based on anatomical properties Hossain et al.[22]

We adopt the distance $d^k_{n,s}$ as a matching weight at each area; short and long distances mean high and low matching weights respectively.

Finally, the sum of distances for all areas are calculated by the following equation,

$$D_{n,s} = \sum_{k=1}^{K} d_{n,s}^{k} \quad (7)$$

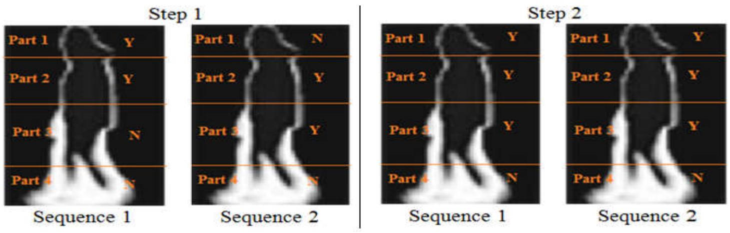

Fig.4 Part selection approach

5. RESULT ANALYSIS AND DISSUASION

We perform weighted integration of selected parts technique on GEnI feature and use K-nearest neighbor classifier. Now a days, gait recognition take the attention of researchers and there is some existing gait recognition methods. J. Han, and B. Bhanu[14] in their work they used PCA,LDA on GEI. Liu Z et al.[19] in their work they used baseline algorithm on GEI. Makihara Y et al.[24] used whole gait DFT feature in their work.Hossainet al. [22] used part based approach in their work. The result of some existing gait recognition methods and our proposed method is given in theTable 3.

Table 3 Classification rate comparison of some existing methods and dynamic parts selection +GEnI method at rank -1

Methods	Recognition Rate(in Rank-1)
PCA+LDA+GEI[14]	**63.17%**
Baseline+GEI[19]	**60.75%**
Whole DFT[24]	**65.59%**
Part-based(without weightening)[22]	**65.99%**
PCA+LDA+GEnI[7]	**70.97%**
Proposed dynamic partsselection+GEnI	**71.026%**

The correct recognition rate at rank-1 of some existing gait recognition methods and proposed dynamic parts selection + GEnI approach is given in the Fig.5 bellow.

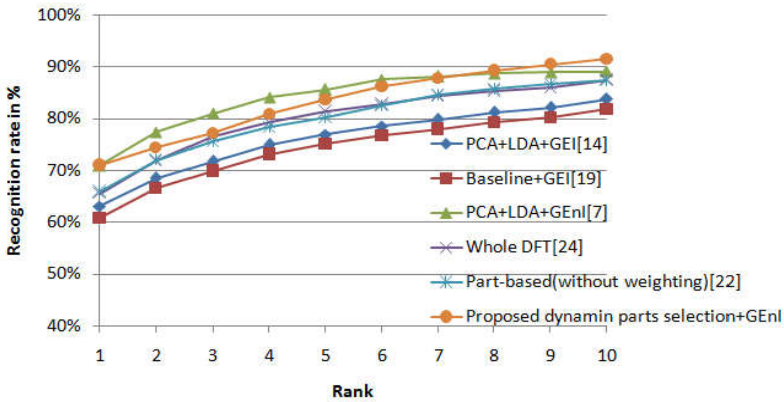

Fig.5Correct Classification Rate(CCR)comparison of some existing methods and proposed dynamic parts selection + GEnIapproach

6. CONCLUTION AND FUTURE WORK

This paper represents human gait with Gait Entropy Image to highlight most dynamic feature of body parts. No one can conceal gait but different covariate affects human gait at different situation.

Representation of gait with GEnI is able to overcome the variation of gait that generated from locomotion and clothing variations by highlighting the dynamic features. We divide the human body into eight unequal parts with some overlapping parts, that bears better performance regarding of some existing gait identification techniques using the whole gait imageand equal part based techniques.Dynamic parts selection improves the performance of gait identification as well as this approach shows the contribution of each part to the identification. With dynamic parts selection we overcome the existing approach of discarding some predefine parts[21] as those parts may contribute to the identification process significantly.In future, we want to apply the proposed approach on large real world data sets with clothing variations. We want to apply the above methods on other existing data sets like CASIA Gait Database(A, B, C, D) , HID-UMD database. We would like to analysis impact of different types classifier on correct classification.

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