Gait Energy Image Representation: Comparative Performance Evaluation on USF HumanID Database

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Abstract

In this paper, a new spatio-temporal gait representation, called Gait Energy Image (GEI), is proposed to characterize human walking properties for individual recognition by gait. To address the problem of the lack of training templates, we expand the training templates by analyzing the human silhouette distortion under various conditions. Principal component analysis and multiple discriminant analysis are used for learning features from the expanded GEI training templates. We compare the proposed GEI based gait recognition approaches with other gait recognition approaches on USF HumanID Database. Experimental results show that the proposed GEI is an effective and efficient gait representation for individual recognition, and the proposed approach achieves highly competitive performance with respect to current gait recognition approaches.

1. Introduction

Current human recognition methods, such as fingerprints, face or iris biometrics, generally require a cooperative subject, views from certain aspects and physical contact or close proximity. These methods can not reliably recognize non-cooperating individuals at a distance in real-world changing environmental conditions. Moreover, in various applications of personal identification, many established biometrics can be obscured. Gait, which concerns recognizing individuals by the way they walk, has been an important biometric without the above-mentioned disadvantages. In recent years, various approaches have been proposed for human recognition by gait analysis. These approaches can be divided into two categories: model-based approaches and model-free approaches.

Model-based gait recognition approaches focus on recovering a structural model of human motion. Niyogi and Adelson [12] make an initial attempt in a spatiotemporal (XYT) volume. They find the bounding contours of the walker, and fit a simplified stick model on them. A characteristic gait pattern in XYT is generated from the model parameters for recognition. Yoo et al. [19] estimate hip and knee angles from body contour by linear regression analysis. Then trigonometric-polynomial interpolant functions are fitted to the angle sequences, and the parameters so-obtained are used for recognition. In Lee and Grimson's work [9], human silhouette is divided into local regions corresponding to different human body parts, and ellipses are fitted to each region to represent the human structure. Spatial and spectral features are extracted from these local regions for recognition and classification. Bhanu and Han [2] propose a kinematic-based approach to recognize individuals by gait. The 3D human walking parameters are estimated by performing a least squares fit of the 3D kinematic model to the 2D silhouette extracted from a monocular image sequence. Human gait signatures are generated by selecting features from the estimated parameters. To obtain more reliable estimates in the presence of noise, Tanawongsuwan and Bobick [15] reconstruct the human structure by tracking 3D sensors attached on fixed joint positions, which is not applicable in most surveillance applications.

Model-free approaches make no attempt to recover a structural model of human motion. Little and Boyd [10] describe the shape of the human motion with a set of features derived from moments of a dense flow distribution. Shutler et al. [14] include velocity into the traditional moments to obtain the so-called velocity moments (VMs). A human motion image sequence can be represented as a single VM value with respect to a specific moment order instead of a sequence of traditional moment values for each frame. He and Debrunner [6] detect a sequence of feature vectors based on Hu's moments of each motion segmented frame, and the individual is recognized from the feature vector sequence using hidden Markov models (HMMs).

BenAbdelkader et al. [1] use height, stride and cadence for to identify human. Kale et al. [8] choose the width vector from the extracted silhouette as the representation of gait. Continuous HMMs are trained for each person and then used for gait recognition.

Figure 1. Examples of normalized and aligned silhouette frames in a human walking sequence. The rightmost image is the average silhouette image over the whole sequence - Gait Energy Image (GEI).

Murase and Sakai [11] propose a template matching method to calculate the spatio-temporal correlation in a parametric eigenspace representation for gait recognition. Huang et al. [7] extend this approach by combining transformation based on canonical analysis, with eigenspace transformation for feature selection. Similarly, Wang et al. [18] generate boundary distance vector from the original human silhouette contour as the template, which is used for gait recognition via eigenspace transformation.

As a direct template matching approach, Phillips et al. [13] measure the similarity between the gallery sequence and the probe sequence by computing the correlation of corresponding time-normalized frame pairs. Similarly, Collins et al. [4] first extract key frames from a sequence, and the similarity between two sequences is computed from normalized correlation. Tolliver and Collins [17] cluster human silhouette of the training sequence into k prototypical shapes. In the recognition procedure, the silhouettes in a testing sequence are also classified into k prototypical shapes that are used to compare with those in the training sequence.

In this paper, we propose a new spatio-temporal gait representation, Gait Energy Image (GEI), for individual recognition. Unlike other gait representations [7, 3] which consider gait as a sequence of templates, GEI represents human motion in a single image while preserving temporal information. We also propose a statistical approach to learn and recognize individual gait properties from the limited training GEI templates.

2. Gait Energy Image Representation

Regular human walking can be considered as cyclic motion where human motion repeats at a stable frequency. Some gait recognition approaches extract features from the correlation of all the frames in a walking sequence without considering their order [11, 7, 18]. Other approaches extract features from each frame and compose a feature sequence for the human walking sequence [10, 14, 6, 1, 8, 13, 4, 17]. During the recognition procedure, they either match the extracted statistics from the feature sequence, or match the features between the corresponding pairs of frames in two sequences that are time-normalized with respect to their cycle lengths. The assumption here is that the order of the poses in human walking cycles is the same, i.e., the limbs move forward and backward in a similar way among different people. The difference exists in the phases of pose changes in a walking cycle, the extend of limbs, and the shape of the torso, etc. As the order of pose changes in human walking is generally not considered in gait recognition approaches, it is possible to compose a spatio-temporal template in a single image instead of a ordered image sequences as usual.

We use a silhouette extraction procedure and begin with the extracted binary silhouette image sequences. The preprocessing procedure includes size normalization - fitting silhouette height to the fixed image height, and sequential horizontal alignment - centering the upper half silhouette part with respect to their horizontal centroid. Figure 1 shows examples of preprocessed silhouettes in a human walking sequence. The rightmost image is the average silhouette image over the whole sequence. As expected, the average silhouette image reflect the major shape of the human silhouettes and their changes over the sequence. The pixel with higher intensity value mean that human body occur more frequently at this position. Therefore, we refer to this average silhouette image as Gait Energy Image (GEI).

Given a size-normalized and horizontal-aligned human walking binary silhouette sequence $B(x, y, t)$, the grey-level GEI $G(x, y)$ is defined as follows

$$G(x, y) = \frac{1}{N} \sum_{t=1}^{N} B(x, y, t), \qquad (1)$$

where N is the sequence length, t is the frame number of the sequence, x and y are values in 2D image coordinate.

GEI has several advantages over the representation of binary silhouette sequence. As an average template, GEI is not sensitive to incidental silhouette errors in individual frames. The robustness could be further improved if we discard those pixels with the energy values lower than a threshold. Moreover, with such a 2D template, we do not need to divide the silhouette sequence into cycles and perform time normalization with respect to the cycle length. Therefore, the errors occuring in these procedures can be therefore avoid.

Compared with the binary silhouette sequence, the information loss of GEI is obvious. For a pixel in GEI, we only know the frequency with which the silhouette occurs at this position over the whole sequence. However, we may partly reconstruct the original silhouette sequence from the GEI with the knowledge of regular human walking. For example, for a pixel near the outline of the leg area, its GEI value shows that silhouette occurs at this location in 20 frames out of 100 frames. Using the common sense, we know that 20 frames should be those frames where human stride instead of standing straight, if noise is not considered. Similarly, we can allocate the GEI values in most other leg/arm areas to corresponding frames in the silhouette sequence. In general, the energy changes in the torso and head area can be considered as noise. Although the knowledge is not enough to completely reconstruct the original silhouette sequence, GEI still keeps the major shape of human walking and reflect the major shape changes during walking. Actually, it is difficult to analyze how and in what degree the information loss affects the discriminant power of GEI as a template for individual recognition. We will evaluate this issue in our experiments by comparing the recognition performance with other gait representation.

3. Human Recognition Using GEI Templates

Human walking sequences for training are limited in real surveillance applications. Because each sequence is represented as one GEI template, the number of training GEIs for each individual might limited to several or even one. Therefore, we have to develop approaches to recognize individuals from the limited templates.

3.1. Direct GEI Matching

One possible approach is recognizing individuals by measuring the similarity between the gallery and probe templates. Given GEIs of two gait sequences, $G_1(x,y)$ and $G_2(x,y)$, their distance can be measured by calculating their normalized matching error:

$$D(G_1,G_2)=\frac{\sum_{x,y}|G_1(x,y)-G_1(x,y)|}{\sum_{x,y}G_1(x,y)\sum_{x,y}G_2(x,y)}, \quad (2)$$

where $\sum_{x,y}|G_1(x,y)-G_1(x,y)|$ is the matching error between two GEIs, $\sum_{x,y}G_1(x,y)$ and $\sum_{x,y}G_2(x,y)$ are total energy in two GEIs, respectively.

This direct template matching approach is sensitive to distortion in scale and transformation. Recognition by learning may recover the inherent property in templates from an individual and therefore insensitive to silhouette distortion. However, with one GEI template per individual, learning cannot be performed. Even with several templates per individual, if they are from similar conditions, the learning results may be overfit to the training templates.

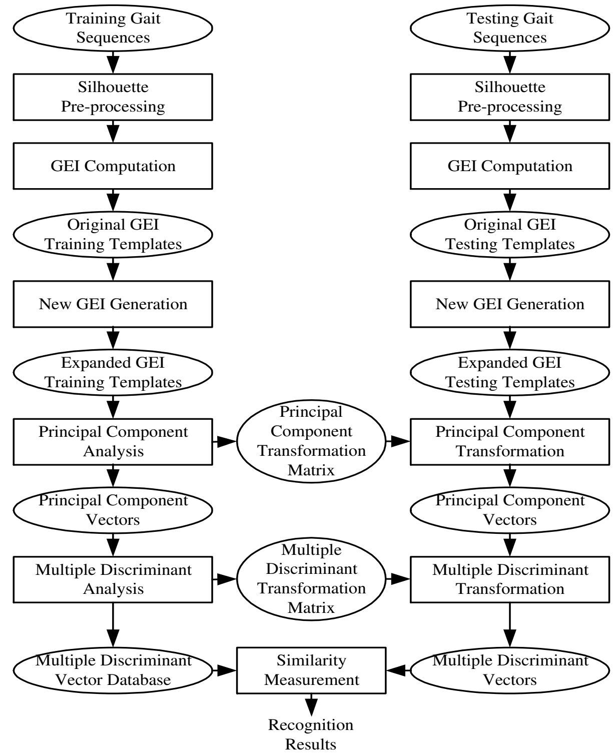

Figure 2. System diagram of individual recognition using the proposed statistical GEI feature matching approach.

3.2. Statistical GEI Feature Matching

In this section, we propose a statistical GEI feature matching approach for individual recognition from limited GEI templates. First, we generate new templates from the limited training templates according to a distortion analysis. Next, statistical features are learned from the expanded training templates by principal component analysis (PCA) to reduce the dimension of the template and multiple discriminant analysis (MDA) to achieve better class separability. The individual is recognized by the learned features. The system diagram of the training and recognition procedure is shown in Figure 2.

3.2.1 Generating New Templates from Limited Training Templates

Various factors have effect on silhouettes extracted from the same person: shoe and cloth, walking surface, camera view, and shadow, etc. Shoe, surface and shadow affect the bottom part of silhouettes. In addition, shoe and surface also change the human walking style. Clothes affects the shape of silhouettes. If the camera view changes slightly, there will be slight changes in silhouettes; if the camera view changes a lot, the extracted silhouettes may be totally different which may cause recognition to fail.

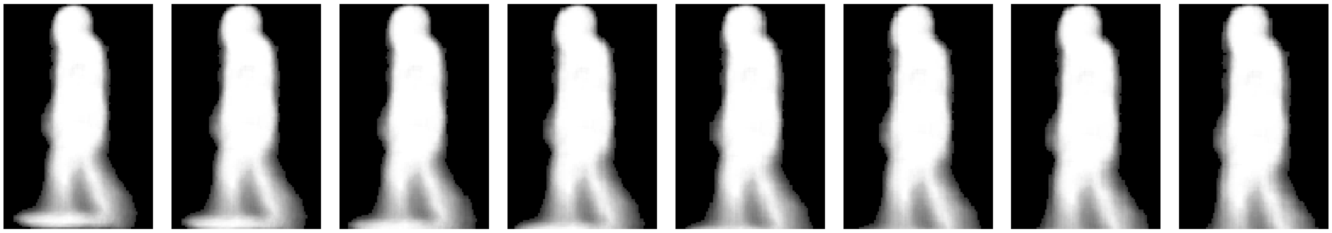

Figure 3. Examples of new GEI templates generated from the original template. The leftmost template is the original template, other templates are sequentially generated by cutting the bottom portion (2 rows in this example) of the previous template and fitting it to the original template size.

Among these factors, slight camera view changes may be neglected. The silhouette shape distortion incurred by the difference of clothes is irregular distortion, which occurs in the upper body, lower body or both, and make body parts fatter or thinner. Thus, it is difficult to model the distortion incurred by the difference of clothes. Similarly, different shoes and walking surfaces incur global distortions in GEI which are also difficult to model. Now we consider the common distortion incurred by the difference of shoe, surface and shadow which generally occurs in the bottom part of the GEI template. These distortions are local distortions which make the bottom part of the GEI template unreliable. If we generate new templates which are insensitive to the distortion in their bottom parts, the learned template properties will be insensitive to this kind of distortion.

The new GEI templates are generated as illustrated in Fig 3. First, we determine the range of the distortion area, e.g., n rows from the bottom row of the original GEI. Then, we cut a portion of the area from the bottom, and fit it to the original GEI size to obtain a new template. By repeating this step until reaching the upper row of the distortion area, we will obtain a series of new templates. From this procedure, we can not only obtain enough templates for each individual to learn the walking properties, but also decrease the sensitivity of the recognition results to the distortion by shadow, shoe and surface each of which occurs in the bottom part of GEI templates.

3.2.2 Learning Templates by Component Analysis and Discriminants

Once we obtain a series of training GEI templates for each individual, the problem of their excessive dimensionality occurs. To reduce their dimensionality, there are two classical approaches of finding effective linear transformations by combing features - Principal Component Analysis (PCA) and Multiple Discriminant Analysis (MDA). As described in [5], PCA seeks a projection that best represents the data in a least square sense, while MDA seeks a projection that best separates the data in a least-square sense. Huang et al. [7] combine PCA and MDA to achieve the best data representation and the best class separability simultaneously. In this paper, the learning procedure follows this combination approach.

Given n d-dimensional training templates $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$, PCA minimizes the criterion function

$$J_{d'} = \sum_{k=1}^{n} ||(\mathbf{m} + \sum_{i=1}^{d'} a_{ki}\mathbf{e}_i) - \mathbf{x}_k||^2, \tag{3}$$

where $d' < d$, $\mathbf{m} = \frac{1}{n}\sum_{k=1}^{n}\mathbf{x}_k$, and $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_{d'}\}$ are a set of unit vectors. $J_{d'}$ is minimized when $\mathbf{e}_1$, $\mathbf{e}_2$, ..., and $\mathbf{e}_{d'}$ are the d' eigenvectors of the scatter matrix S having the largest eigenvalues. The d'-dimensional principal component vector of $\mathbf{x}_k$ is obtained by multiplying the transformation matrix $[\mathbf{e}_1, ..., \mathbf{e}_{d'}]$

$$\mathrm{y}_k = [a_1, ..., a_{d'}]^T = [\mathbf{e}_1, ..., \mathbf{e}_{d'}]^T \mathrm{x}_k, \quad k = 1, ..., n. \tag{4}$$

Although PCA finds components that are useful for representing data, there is no reason to assume that these components must be useful for discriminating between data in different classes because PCA does not consider the class label of training templates. Multiple discriminant analysis (MDA) seeks a projection that are efficient for discrimination. Suppose that the n d'-dimensional transformed training templates $\{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_n\}$ belong to c classes. MDA seeks a transformation matrix W that in some sense maximizes the ratio of the between-class scatter S_B to the within-class scatter S_W:

$$J(W) = \frac{|\tilde{S}_B|}{|\tilde{S}_W|} = \frac{|W^T S_B W|}{|W^T S_W W|}. \tag{5}$$

$J(W)$ is maximized when the columns of W are the generalized eigenvectors that correspond to the largest eigenvalues in

$$S_B \mathbf{w}_i = \lambda_i S_W \mathbf{w}_i. \tag{6}$$

There are no more than $c-1$ nonzero eigenvalues, and the corresponding eigenvectors $\mathbf{v}_1$,...,$\mathbf{v}_{c-1}$ form transformation matrix. The $(c-1)$-dimensional multiple discriminant vector of $\mathbf{z}_k$ is obtained by multiplying the transformation matrix $[\mathbf{v}_1, ..., \mathbf{v}_{c-1}]$

$$\mathrm{z}_k = [\mathbf{v}_1, ..., \mathbf{v}_{c-1}]^T \mathrm{y}_k, \quad k = 1, ..., n. \tag{7}$$

Table 1. Twelve experiments designed for individual recognition in USF HumanID database.

Experiment Label	Size of Probe Set	Difference between Gallery and Probe Sets
A	71	View
B	41	Shoe
C	41	View and Shoe
D	70	Surface
E	44	Surface and Shoe
F	70	Surface and View
G	44	Surface, Shoe and View
H	70	Briefcase
I	47	Shoe and Briefcase
J	70	View and Briefcase
K	33	Time, Shoe and Clothing
L	33	Surface and Time

The obtained feature vectors compose the feature database for individual recognition.

3.2.3 Individual Recognition

Given the GEI template $\tilde{\mathbf{x}}$ of a query gait sequence, a set of n_q templates $\{\tilde{\mathbf{x}}_1, ..., \tilde{\mathbf{x}}_{n_q}\}$ are generated according to the procedure described in Section 3.2.1. After the principal component transformation and multiple discriminant transformation, we obtain a set of feature vectors $\{\tilde{\mathbf{z}}_1, ..., \tilde{\mathbf{z}}_{n_q}\}$ for this test gait sequence. The feature distance between the query gait sequence and each class in the feature database can be given by the minimum distance between query and training feature vector pairs as follows

$$Distance_i = \min_{\mathbf{z} \in \mathcal{D}_i} \min_{j=1}^{n_q} \sum_{k=1}^{c-1} |\tilde{z}_{jk} - z_k|, \quad i = 1, ..., c. \quad (8)$$

After the distances for each class are obtained, they are ranked in an ascending order where the class with the smallest distance is the best match of the query gait sequence.

4. Experimental Results

Our experiments are carried out on the USF HumanID gait database. This database consists of persons walking in elliptical paths in front of the cameras. For each person, there are up to 5 covariates: viewpoints - Left/Right, shoe types - A/B, surface types - grass/concrete, carrying conditions - with/without a briefcase, and time and clothing. Twelve experiments are designed for individual recognition as shown in Table 1. The gallery set contains 71 sequences from 71 subjects. The GEIs of several sequences in the gallery set and their corresponding sequences in probe sets A-L are shown in Figure 4.

Table 2. Comparison of recognition performance of Rank 1 among different approaches on silhouette sequence version 1.7 (Legends: USF - direct frame shape matching [13]; DGEI - direct GEI matching, this paper; CMU - key frame shape matching [4]; SPS1/SPS2 - clustered frame shape matching with two criteria [17]; SGEI - statistical GEI feature matching, this paper.)

	USF	DGEI	CMU	SPS1	SPS2	SGEI
A	79%	99%	87%	82%	85%	90%
B	66%	83%	81%	66%	81%	90%
C	56%	73%	66%	54%	60%	73%
D	29%	18%	21%	20%	23%	41%
E	24%	14%	27%	21%	25%	40%
F	30%	11%	42%	45%	11%	27%
G	10%	10%	23%	21%	21%	38%

Table 3. Comparison of recognition performance of Rank 5 among different approaches on silhouette sequence version 1.7 (Same legends as in Table 2)

	USF	DGEI	CMU	SPS1	SPS2	SGEI
A	96%	100%	100%	98%	90%	99%
B	80%	93%	90%	90%	87%	93%
C	76%	93%	83%	81%	80%	93%
D	61%	55%	59%	46%	52%	68%
E	52%	52%	50%	43%	43%	69%
F	45%	47%	53%	46%	48%	58%
G	33%	52%	43%	43%	44%	60%

Phillips et al. [13] propose a baseline approach to extract human silhouette and recognize the individual in this database. For comparison, they provide extracted silhouette data which can be found at the website http://marathon.csee.usf.edu/GaitBaseline/. Our experiments begin with these extracted binary silhouette data (version 1.7 and 2.0). The experimental results are shown in Table 2, 3, 4 and 5 as well as comparison with other approaches for individual recognition by gait. In these tables, rank1 means that only the first subject in the retrieval rank list is recognized as the same subject as the query subject, and rank5 means that the first five subjects are all recognized as the same subject as the query subject. The performance in these tables is the recognition rate under these two definitions.

4.1. Recognition Results by Direct GEI Matching

To evaluate the effectiveness of GEI as a gait representation, we carry out experiments of individual recog-

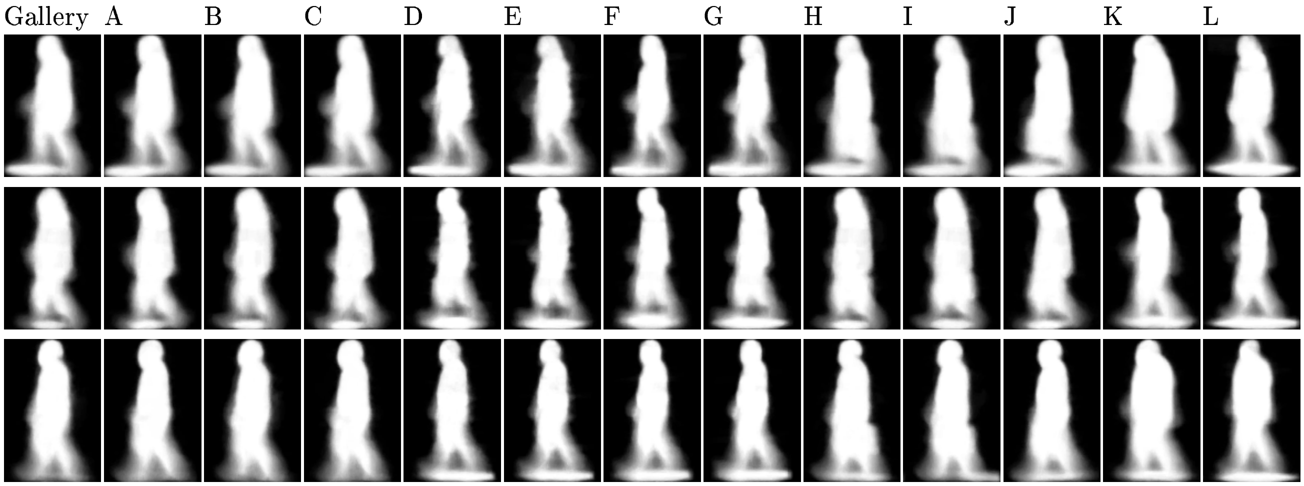

Figure 4. GEI examples in USF HumanID database (GEIs in each row represent the same person walking under different conditions; GEIs in different rows represent different persons).

Table 4. Comparison of recognition performance of Rank 1 among different approaches on silhouette sequence version 2.0 (SPS - clustered frame shape matching [16]; other legends are the same as in Table 2).

	USF	DGEI	SPS	SGEI
A	87%	94%	97%	92%
B	81%	88%	90%	90%
C	54%	85%	80%	73%
D	39%	32%	44%	47%
E	33%	36%	41%	52%
F	29%	23%	36%	29%
G	26%	21%	36%	43%
H	78%	100%	74%	67%
I	71%	83%	72%	67%
J	60%	41%	56%	45%
K	15%	13%	64%	29%
L	19%	10%	40%	29%

Table 5. Comparison of recognition performance of Rank 5 among different approaches on silhouette sequence version 2.0 (SPS - clustered frame shape matching [16]; other legends are the same as in Table 2).

	USF	DGEI	SPS	SGEI
A	93%	100%	99%	99%
B	83%	93%	98%	98%
C	68%	93%	93%	98%
D	58%	53%	76%	73%
E	52%	50%	68%	74%
F	46%	44%	67%	67%
G	45%	45%	64%	69%
H	79%	100%	94%	91%
I	76%	88%	87%	86%
J	70%	78%	90%	84%
K	30%	19%	73%	52%
L	33%	39%	73%	52%

nition by direct matching between GEI templates according to the distance metric give by Equation (2). As we mentioned in Section 1, Phillips et al. [13] measure the similarity between the gallery sequence and the probe sequence by computing the correlation of corresponding time-normalized frame pairs. This approach can be viewed as a typical direct matching approach between regular gait silhouette sequences. We compare the recognition performance between their approach (USF) and our direct GEI matching approach (DGEI) as shown in Table 2 and 3.

The left part of Table 2 and 3 shows the recognition performance of USF and DGEI approaches on silhouette version 1.7. It is shown that our DEGI approach achieves much better results in experiments A-C. In these experiments, the difference between gallery and probe data exists in view, shoe or both, which incur little distortion in extracted silhouette. This means that GEI is less sensitive to this kind of distortion than regular gait silhouette sequence.

Although the rank1 performance of DGEI and USF are both not good in experiments D-G, our DEGI is worse than that of USF (See Table 2). The probe sets in experiments D-G have the common difference of surface with respect to the gallery set. As we discussed previously, the distortion incurred by surface difference is relatively large. For example, if the same person walks at different surface, the extracted silhouettes may have different shadows. In addition, silhouette from walking sequence on the grass surface may miss the bottom part of the foot because it could be covered by the grass. In this case, silhouette height normalization errors occur, and the silhouette so-obtained may have different scale with respect to the silhouette

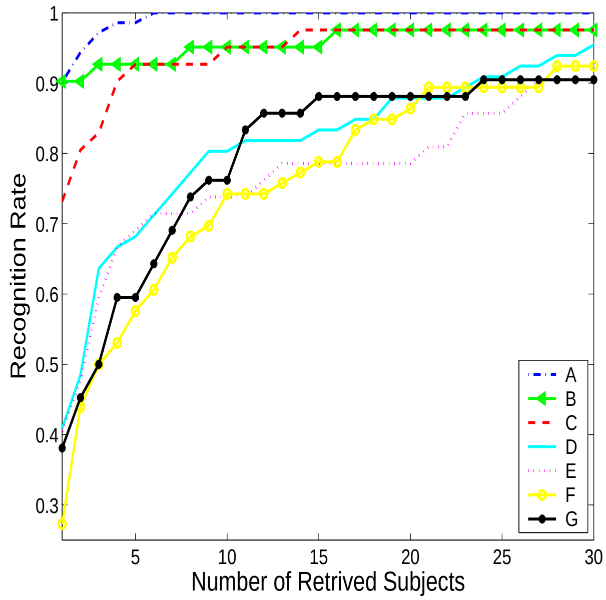

Figure 5. CMC curves of our SGEI approach on Experiments A-G (silhouette version 1.7).

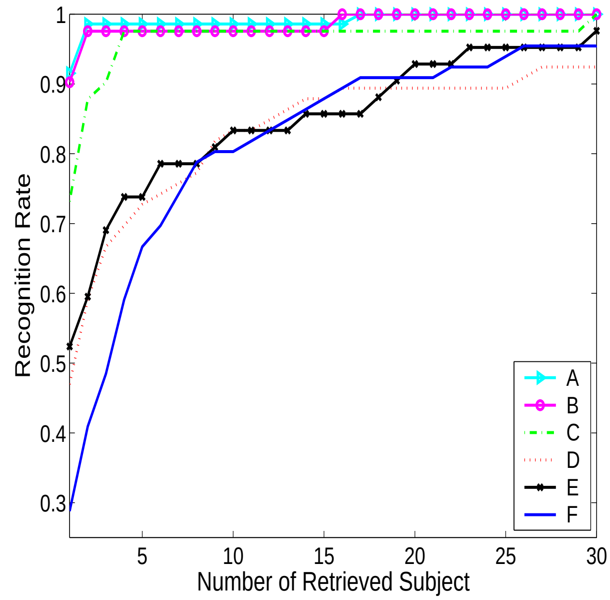

Figure 6. CMC curves of our SGEI approach on Experiments A-F (silhouette version 2.0).

on other surfaces. It is shown that the GEI is sensitive to this kind of distortion with respect to the regular silhouette sequence. However, the rank5 performance of our DGEI is similar to that of USF in experiments D-G (See Table 3). This shows that GEI is competitive with regular silhouette sequence because the rank1 results are not reliable and more ranked subjects should be considered. Another reason of the worse rank1 performance of DGEI (See Table 3) is that the silhouettes of version 1.7 are not well-aligned.

Comparing the performance of USF and DGEI on silhouettes of version 2.0 in Table 4 and 5, we find that the rank1 and rank5 performance of our DGEI approach is better that of the USF approach in most experiments, especially in the less distorted data sets A-C and H-I. Notice that the silhouette of version 2.0 is well-aligned. This shows that GEI is an effective gait representation on well-aligned silhouette data. In addition, GEI is an efficient gait representation because it saves space and further computation time with respect to the regular gait silhouette sequence.

4.2. Recognition Results by Statistical GEI Feature Matching

Table 2, 3, 4 and 5 show that our individual recognition approach by statistical GEI feature matching (SGEI) achieves better recognition results than DGEI in the experiments with large silhouette distortion, i.e., D-G and K-L. In the other experiments with small silhouette distortion, the performance of SGEI is better than that of DGEI in experiments B, C and J, but worse in experiments A, H and I. Thus SGEI slightly sacrifice the performance in experiments with small silhouette distortion while improving the performance in experiments with large silhouette distortion with respect to DGEI.

We compare the performance of SGEI with other approaches published in [13, 4, 17] on silhouette of version 1.7 in Table 2 and 3. It is shown that our approach achieves highly competitive results compared with those approaches. Figure 5 shows the cumulative match characteristic (CMC) curves of SGEI approach on silhouette version 1.7.

We also compare the performance of SGEI with Tolliver et al.'s approach [17, 16] on silhouette of version 2.0 in Table 4 and 5. The SGEI approach is competitive with their approach in experiments A-J, but our performance is worse in K and L. The lower recognition rate may be caused by the more distorted silhouette shape in K and L. As indicated in Figure 4, the appearance of silhouette shape in probe sets K and L has much difference with respect to the gallery set. Therefore, we consider combining temporal templates with GEI templates to improve the recognition performance in the presence of such large silhouette distortion in future. Figure 6 and 7 show the CMC curves of SGEI approach on silhouette version 2.0.

5. Conclusions

In this paper, we propose a new spatio-temporal gait representation, called Gait Energy Image (GEI), for individual recognition by gait. Unlike other gait representation which considers gait as a sequence of templates (poses), GEI represents human motion sequence in a single image while preserving temporal informa-

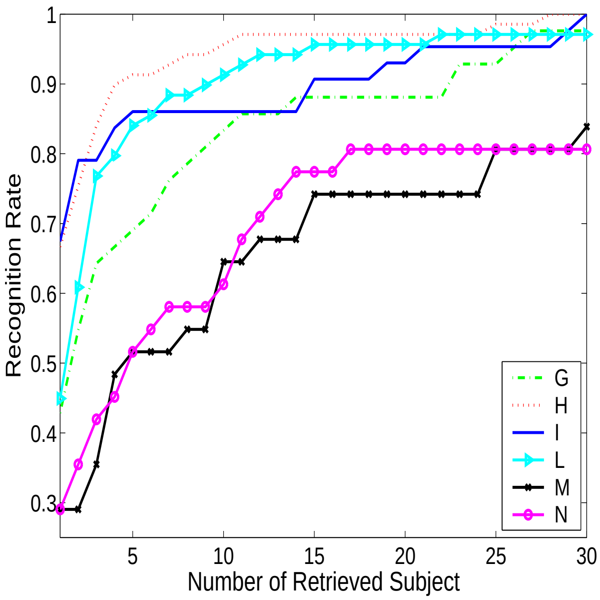

Figure 7. CMC curves of our SGEI approach on Experiments G-L (silhouette version 2.0).

tion. To overcome the limitation of training templates, we generate a series of new GEI templates by analyzing the human silhouette distortion under various conditions. Principal component analysis and multiple discriminant analysis are used for learning features from the expanded GEI training templates. Recognition is then carried out based on the learned features. Experimental results show that (a) GEI is an effective and efficient gait representation which is insensitive to incidental silhouette errors in individual frames, and (b) the proposed recognition approach achieves highly competitive performance with respect to current gait recognition approaches.

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