# Statistical Feature Fusion for Gait-based Human Recognition

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## Abstract

*This paper presents a novel approach for human recognition by combining statistical gait features from real and synthetic templates. Real templates are directly computed from training silhouette sequences, while synthetic templates are generated from training sequences by simulating silhouette distortion. A statistical feature extraction approach is used for learning effective features from real and synthetic templates. Features learned from real templates characterize human walking properties provided in training sequences, and features learned from synthetic templates predict gait properties under other conditions. A feature fusion strategy is therefore applied at the decision level to improve recognition performance. We apply the proposed approach to USF HumanID Database. Experimental results demonstrate that the proposed fusion approach not only achieves better performance than individual approaches, but also provides large improvement in performance with respect to the baseline algorithm.*

## 1 Introduction

Traditional human recognition methods, such as fingerprint, 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 human at a distance in real-world changing environmental conditions. Moreover, in various applications of human 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 the gait recognition process, there are also some challenging problems. In silhouette based gait recognition, the extracted silhouettes are generally very noisy due to the complexity of real world. These incidental silhouette errors make the recognition difficult. Another problem is the lack of gallery gait data. Gait can be affected by clothing, shoes, environmental or physical conditions. However, due to the difficulty of gait data acquisition, the number of gallery sequences for each person is very limited. Even several sequences for some person are available, most of them are from similar conditions. This makes it difficult to recognize individuals under other conditions.

In this paper, the problem of silhouette noise is address by a novel gait representation, gait energy image (GEI), which represents gait in a single image while preserving temporal information and is insensitive to incidental silhouette errors. To address the problem of lacking gallery gait data, we propose a novel approach for human recognition by combining statistical gait features from real and synthetic templates. The fused features not only characterize human walking properties provided in training sequences, but also predict gait properties under other conditions.

## 2 Related Work

In recent years, various approaches have been proposed for human recognition by gait. These approaches can be divided into two major 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 [7] find the bounding contours of the walker, and fit a simplified stick model on them. A characteristic gait pattern in spatiotemporal volume is generated from the model parameters for recognition. Yoo et al. [14] 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. To obtain more reliable estimates in the presence of noise, Tanawongsuwan and Bobick [11] reconstruct the human structure by tracking 3D sensors attached on fixed joint positions.

Model-free approaches make no attempt to recover a structural model of human motion. Little and Boyd [6] describe the shape of the human motion with a set of features derived from moments of a dense flow distribution. Shutler et al. [10] include velocity into the traditional moments to obtain the so-called velocity moments (VMs). BenAbdelkader et al. [1] use height, stride and cadence for to identify human. Kale et al. [5] choose the width vector from the extracted silhouette as the representation of gait, and continuous HMMs are trained for recognition.

Huang et al. [4] propose a template matching approach

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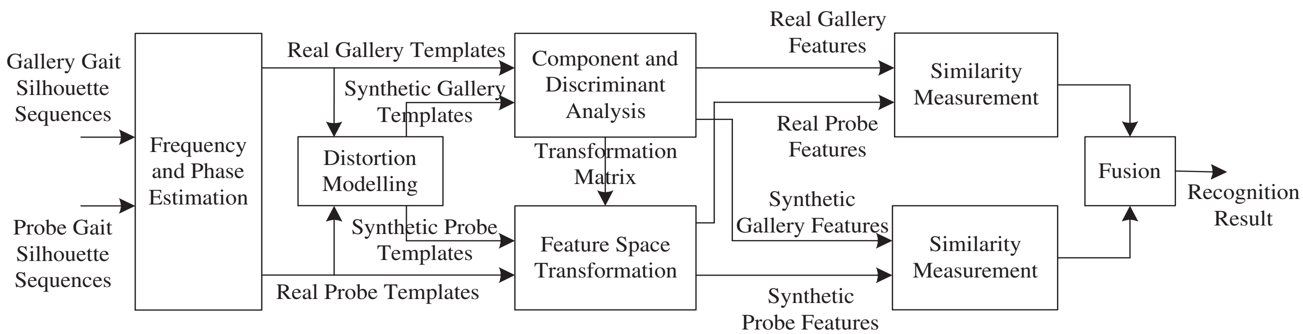


**Figure 1. System diagram of human recognition using proposed statistical feature fusion approach.**

by combining transformation based on canonical analysis, with eigenspace transformation for feature selection. Similarly, Wang et al. [13] generate boundary distance vector from the original human silhouette contour as the template, which is used for gait recognition via eigenspace transformation. Phillips et al. [9] propose a direct template matching approach to measure the similarity between the gallery and probe sequences by computing the correlation of corresponding time-normalized frame pairs. Similarly, Collins et al. [2] first extract key frames from a sequence, and the similarity between two sequences is computed from the normalized correlation on key frames only. Tolliver and Collins [12] cluster human silhouettes of each training sequence into $k$ prototypical shapes. Silhouettes in a testing sequence are also classified into $k$ prototypical shapes that are used to compare with those in training sequences.

# 3 Technical Approach

In this section, we describe the proposed statistical feature fusion approach for gait-based human recognition. In the training procedure, each gallery silhouette sequence is divided into cycles by frequency and phase estimation. Real gait templates are then computed from each cycle, and distorted to generate synthetic gait templates. Next, we perform a component and discriminant analysis procedure on real and synthetic gait templates, respectively. As a result, real features and synthetic features form feature databases, and real and synthetic transformation matrixes will be used to project probe gait templates onto the feature spaces. In the recognition procedure, each probe silhouette sequence is processed in the same way to generate real and synthetic gait templates. These templates are then transformed by real and synthetic transformation matrixes to obtain real and synthetic features, respectively. Probe features are compared with gallery features in the database, and a feature fusion strategy is applied to combine real and synthetic features at the decision level to improve recognition performance. The system diagram is shown in Figure 1.

## 3.1 Gait Frequency and Phase Estimation

Regular human walking can be considered as cyclic motion where human motion repeats at a stable frequency. Therefore, it is possible to divide the whole gait sequence into cycles and study them separately. We assume that silhouette extraction has been performed on original human walking sequences, and begin with the extracted binary silhouette image sequences. The silhouette preprocessing includes size normalization (proportionally resizing each silhouette image so that all silhouettes have the same height) and horizontal alignment (centering the upper half silhouette part with respect to its horizontal centroid). In a preprocessed silhouette sequence, the time series signal of lower half silhouette part size from each frame indicates the gait frequency and phase information. The obtained time series signal consists of few cycles and lots of noise, which lead to sidelobe effect in the Fourier spectrum. To avoid this problem, we estimate the gait frequency and phase by maximum entropy spectrum estimation [6].

## 3.2 Gait Representation

Most gait recognition approaches extract features from each frame and compose a feature sequence for the human walking sequence [1, 2, 4, 5, 6, 9, 10, 12, 13]. 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 poses in human walking cycles is the same, i.e., the limbs move forward and backward in a similar way among normal people. The difference exists in the phase of poses in a walking cycle, the extend of limbs, and the shape of the torso, etc. As the order of poses in regular human walking is generally not considered in the gait recognition process, it is possible to compose a spatio-temporal gait template in a single image instead of an ordered image sequence as usual.

Given a preprocessed binary gait silhouette sequence $B(x, y, t)$, the grey-level gait energy image (GEI) is defined as follows

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

where $N$ is the number of frames in the complete cycle(s) of a silhouette sequence, $t$ is the frame number of the sequence (moment of time), $x$ and $y$ are values in the 2D image coordinate. Figure 2 shows the sample silhouette images in

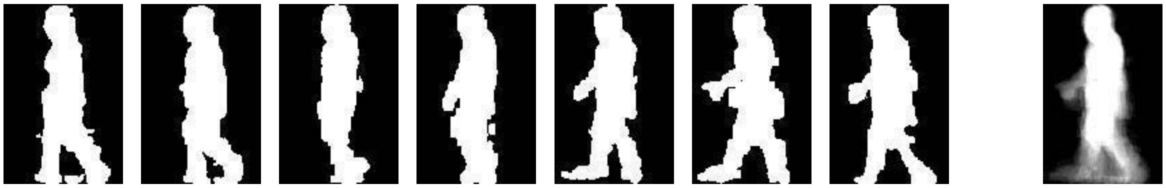

**Figure 2. Sample silhouette images in a gait cycle and the corresponding GEI (the right most image).**

a gait cycle and the right most image is the corresponding GEI. As expected, it reflects major shapes of silhouettes and their changes over the gait cycle. We refer to it as gait energy image because: (a) each silhouette image is the normalized gait (human walking) area; (b) a pixel within the silhouette in a image means that human walking occurs at this position and this moment; (c) a pixel with higher intensity value in GEI means that human walking occurs more frequently at this position (i.e., with higher energy).

GEI has several advantages over the gait representation of binary silhouette sequence. 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 consider the normalized time moment of each frame, and the incurred errors can be therefore avoided.

### 3.3 Real and Synthetic Gait Templates

The number of training sequences for each person is limited (one or several) in real surveillance applications. This makes it difficult to recognize individuals under various conditions. To solve this problem, one solution is directly measuring the similarity between the gallery (training) and probe (testing) templates. However, direct template matching is sensitive to silhouette distortion such as scale and displacement changes. Statistical feature learning may recover inherent properties in training templates from an individual and therefore insensitive to such silhouette distortion. However, with gait templates obtained under similar conditions, the learned features may be overfitting. Therefore, we generate two sets of gait templates, real templates and synthetic templates, to solve the overfitting problem.

The real gait templates for an individual are directly computed from each cycle of the silhouette sequence of this individual. Let $\{R_i\}, i = 1, \ldots, n$, be the real GEI template set of the individual, where $n$ is the number of completes cycles in the silhouette sequence. The first row of Figure 3 shows an example of the real GEI template set from an individual. Note that all the real examples have the similar appearance in the presence of noise.

Although real gait templates provide cues for individual recognition, real gait templates from the same sequence are all obtained under the same conditions. If the condition changes, the learned features may not work well for recognition. Various conditions have effect on silhouette appearance from the same person: walking surface, shoe and clothing, etc. The common silhouette distortion in the lower silhouette part occurs under most conditions. This kind of distortion includes shadows, body parts missing, and sequential silhouette scale changes. For example, silhouettes on the grass surface may miss the bottom part of feet, while silhouettes on the concrete surface may contain additional shadows. In these cases, silhouette size normalization errors occur, and silhouettes so-obtained may have different scales with respect to silhouettes on other surfaces. Therefore, we generate a series of synthetic gait templates that are insensitive to lower silhouette part distortion and small silhouette scale changes as shown in the second row of Figure 3.

Synthetic gait templates are computed from the fundamental GEI template ($R_0 = \frac{1}{n}\sum_{i=1}^{n} R_i$) of a given silhouette sequence as follows. First of all, we select the bottom part distortion area in GEI based on anthropometric data [8]. The length from the bottom of bare foot to the ankle above the sole is approximately $1/24$ of the stature. Considering the height of heelpiece and shadow, we select $1/9$ of the silhouette height as approximate estimate of the distortion area for all GEI templates in different conditions (A-L). In the first step, we cut $k$ rows from the bottom of the template (e.g., size of $128 \times 88$), and proportionally resize the remaining template ($128 - k$ rows) to a template of 128 rows by using nearest neighbor interpolation. Cutting left and right borders, we will obtain a new template with the size of $128 \times 88$. Repeating this step ($2k$ rows, $3k$ rows, ...) until reaching the upper row of the distortion area, we will obtain a set of synthetic templates $\{S_i\}, i = 1, \ldots, m$. The synthetic templates expanded from the same $R_0$ have the same global shape properties but different bottom parts and different scales. Therefore, they provide cues for individual recognition that are insensitive to silhouette scale changes and lower silhouette part distortion.

With the obtained real and synthetic gait templates, a statistical feature extraction method is used for learning gait features from real and synthetic templates, respectively. Features learned from real templates characterize human walking properties provided in training sequences, and features learned from synthetic templates predict gait properties under other conditions.

### 3.4 Statistical Feature Extraction

To achieve the best data representation and the best class separability simultaneously, we extract features from gait templates by principal component analysis (PCA) followed by multiple discriminant analysis (MDA) [4].

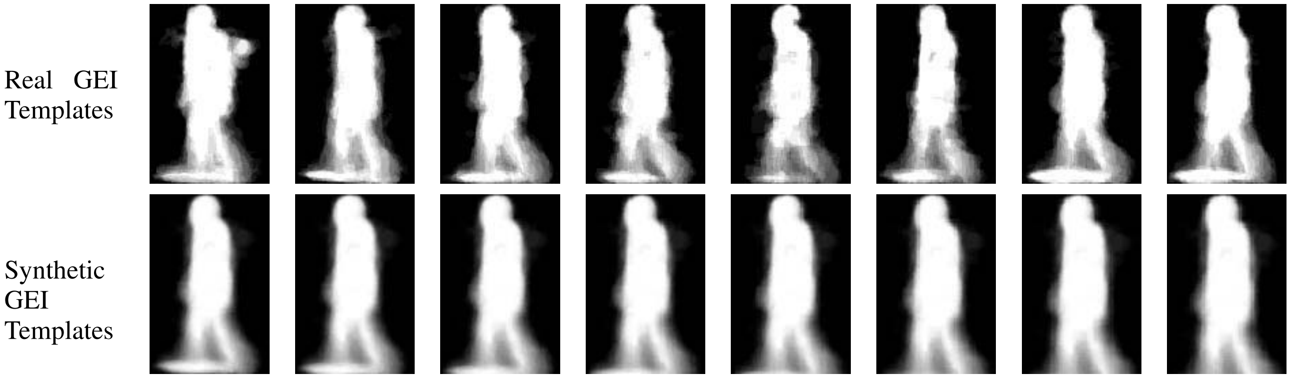


**Figure 3. An example of real and synthetic gait templates generated from a silhouette sequence.**

PCA seeks a projection that best represents the data [3]. Given the $d$-dimensional training template set $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_{n_t}\}$, the $d'$-dimensional feature vector $\mathbf{y}_k$ is obtained as follows

$$\mathrm{y}_k = M_{pca}\mathrm{x}_k, \quad k = 1, ..., n_t \tag{2}$$

where $M_{pca}$ is the transformation matrix obtained by PCA on $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_{n_t}\}$, and $n_t$ is the number of the gait templates from all people in the training database. MDA seeks a projection that best separates the data. Assuming that $\{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_{n_t}\}$ belong to $c$ classes, the $(c-1)$-dimensional feature vector $\mathbf{z}_k$ is obtained as follows

$$\mathrm{z}_k = M_{mda}\mathrm{y}_k, \quad k = 1, ..., n_t \tag{3}$$

where $M_{mda}$ is the transformation matrix obtained by MDA on $\{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_{n_t}\}$.

For each training gait template, its gait feature vector is obtained as follows

$$\mathrm{z}_k = M_{mda}M_{pca}\mathrm{x}_k = T\mathrm{x}_k, \quad k = 1, ..., n_t \tag{4}$$

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

### 3.5 Feature Fusion for Individual Recognition

We train the real gait templates and synthetic gait templates separately for feature extraction. Let $\{\mathbf{r}\}$ be the set of real feature vectors extracted from real training gait templates, and $T_r$ is the corresponding real transformation matrix. Similarly, let $\{\mathbf{s}\}$ be the set of synthetic feature vectors extracted from synthetic training gait templates, and $T_r$ is the synthetic transformation matrix. The class centers for $\{\mathbf{r}\}$ and $\{\mathbf{s}\}$ are given as follows

$$\mathrm{m}_{ri} = \frac{1}{n_i}\sum_{\mathbf{r}\in\mathcal{R}_i}\mathbf{r} \quad \text{and} \quad \mathrm{m}_{si} = \frac{1}{m_i}\sum_{\mathbf{s}\in\mathcal{S}_i}\mathbf{s}, \quad i = 1, ..., c \tag{5}$$

where $c$ is the number of classes (individuals) in the database, $\mathcal{R}_i$ is the set of real feature vectors belonging to the $i$th class, $\mathcal{S}_i$ is the set of synthetic feature vectors belonging to the $i$th class, $n_i$ is the number of feature vectors in $\mathcal{R}_i$, and $m_i$ is the number of feature vectors in $\mathcal{S}_i$. Assuming that feature vectors in each class are Gaussian distributed with the same covariance matrix $\Sigma = \sigma I$, Bayesian classifier becomes minimum Euclidean classifier which will be used in the following individual recognition.

Given a probe gait silhouette sequence $P$, we follow the procedure in Section 3.3 to generate real gait templates $\{R_j\}$, $j = 1, \ldots, n$ and synthetic gait templates $\{S_j\}$, $j = 1, \ldots, m$. The corresponding real and synthetic feature vector sets are obtained as follows

$$\{\hat{\mathcal{R}}_P\}: \quad \hat{\mathrm{r}}_j = T_r R_j, \quad j = 1, ..., n$$
$$\{\hat{\mathcal{S}}_P\}: \quad \hat{\mathrm{s}}_j = T_s S_j, \quad j = 1, ..., m$$

For the classifier based on real gait templates, we define

$$D(\hat{\mathcal{R}}_P, \mathcal{R}_i) = \frac{1}{m}\sum_{j=1}^{m}||\hat{\mathrm{r}}_j - \mathrm{m}_{ri}||, \quad i = 1, ..., c \tag{6}$$

We assign $P \in \omega_k$ if

$$D(\hat{\mathcal{R}}_P, \mathcal{R}_k) = \min_{i=1}^{c} D(\hat{\mathcal{R}}_P, \mathcal{R}_i). \tag{7}$$

For the classifier based on synthetic gait templates, we define

$$D(\hat{\mathcal{S}}_P, \mathcal{S}_i) = \min_{j=1}^{n}||\hat{\mathrm{s}}_j - \mathrm{m}_{si}||, \quad i = 1, ..., c \tag{8}$$

We assign $P \in \omega_k$ if

$$D(\hat{\mathcal{S}}_P, \mathcal{S}_k) = \min_{i=1}^{c} D(\hat{\mathcal{S}}_P, \mathcal{S}_i). \tag{9}$$

For the fused classifier, we define

$$D(\{\hat{\mathcal{R}}_P, \hat{\mathcal{S}}_P\}, \{\mathcal{R}_i, \mathcal{S}_i\}) = \frac{c(c-1)D(\hat{\mathcal{R}}_P, \mathcal{R}_i)}{2\sum_{i=1}^{c}\sum_{j=1,j\neq i}^{c} D(\mathcal{R}_i, \mathcal{R}_j)} + \frac{c(c-1)D(\hat{\mathcal{S}}_P, \mathcal{S}_i)}{2\sum_{i=1}^{c}\sum_{j=1,j\neq i}^{c} D(\mathcal{S}_i, \mathcal{S}_j)}, \quad i = 1, ..., c \tag{10}$$

where $2\sum_{i=1}^{c}\sum_{j=1,j\neq i}^{c} D(\mathcal{R}_i, \mathcal{R}_j)/c(c-1)$ is the average distance between real feature vectors of every two classes in the database which is used to normalize $D(\hat{\mathcal{R}}_P, \mathcal{R}_i)$, and $2\sum_{i=1}^{c}\sum_{j=1,j\neq i}^{c} D(\mathcal{S}_i, \mathcal{S}_j)/c(c-1)$ has the similar meaning. We assign $P \in \omega_k$ if

$$D(\{\hat{\mathcal{R}}_P, \hat{\mathcal{S}}_P\}, \{\mathcal{R}_k, \mathcal{S}_k\}) = \min_{i=1}^{c} D(\{\hat{\mathcal{R}}_P, \hat{\mathcal{S}}_P\}, \{\mathcal{R}_i, \mathcal{S}_i\}). \tag{11}$$

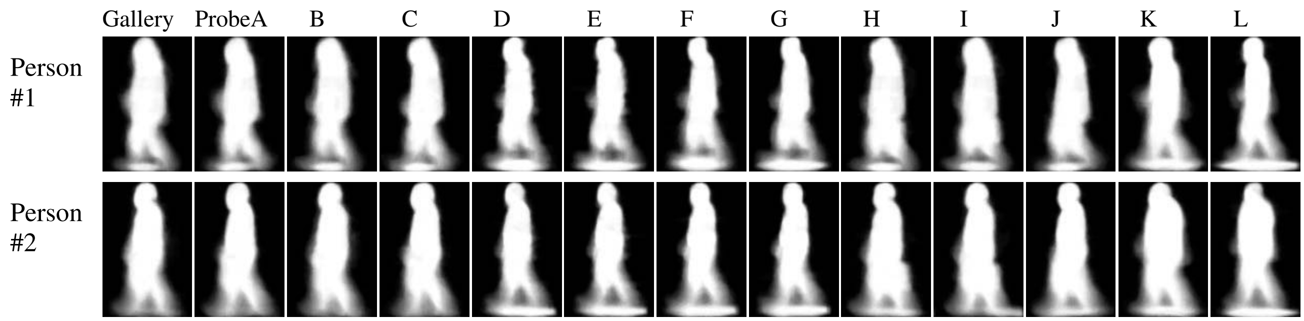


**Figure 4. GEI examples in USF HumanID database.**

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

| Experiment Label | Size of Probe Set | Difference between Gallery and Probe Sets |
|---|---|---|
| A | 122 | View |
| B | 54 | Shoe |
| C | 54 | View and Shoe |
| D | 121 | Surface |
| E | 60 | Surface and Shoe |
| F | 121 | Surface and View |
| G | 60 | Surface, Shoe and View |
| H | 120 | Briefcase |
| I | 60 | Shoe and Briefcase |
| J | 120 | View and Briefcase |
| K | 33 | Time, Shoe and Clothing |
| L | 33 | Surface and Time |

## 4 Experimental Results

Our experiments are carried out on the USF HumanID gait database [9]. This database consists of people walking in elliptical paths in front of the camera. 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 122 sequences. Individuals are unique in the gallery and each probe set, and there are no common sequence among the gallery set and all probe sets. The gait templates ($R_0$ in Section 3.3) of two individuals in the gallery set and their corresponding sequences in probe sets A-L are shown in Figure 4.

Phillips et al. [9] propose a baseline approach to extract human silhouette and recognize people 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 2.1) that are updated on September 5, 2003. The performance of their baseline algorithm are shown in Table 2. Currently, their results are the only public results on the version 2.1 data. In this table, 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 the table is the recognition rate under these two definitions.

We carry out experiments of human recognition by real features, synthetic features and fused features according to rules in (7), (9), and (11), respectively. Table 2 compares the recognition performance of USF baseline algorithm and our proposed approaches. It is shown that the rank1 performance of proposed real feature classifier is better than or equivalent to that of baseline algorithm on all experiments. The rank5 performance of real feature classifier is better than that of baseline algorithm on most experiments but a little worse on experiments D and F. This demonstrate that matching features learned from real gait templates achieves better recognition performance than direct matching between individual silhouette frame pairs in baseline algorithm.

The performance of proposed synthetic feature classifier is significantly better than that of real feature classifier on experiments D-G and K-L. Probe sets in D-G have the common difference of walking surface with respect to the gallery set, and probe set in K-L have the common difference of time with respect to the gallery set. In these probe sets, the silhouette distortion in the lower body part is obvious compared with silhouettes in the gallery set. The experimental results show that the proposed synthetic feature classifier is insensitive to this kind of distortion compared with real feature classifier. However, the proposed synthetic feature classifier sacrifices the performance on experiments H-J where probe sets contain people carrying briefcase where the briefcases occur beyond the selected distortion area.

The fused feature classifier achieves better performance than individual real feature classifier and synthetic classifier in most experiments, and achieves significantly better performance than baseline algorithm in all experiments. It is shown that the fusion approach take advantage of merits in individual features.

Although the proposed fusion approach achieves significantly better results than baseline algorithm, its performance is still not satisfied in the presence of large silhouette distortion such as probe sets K and L. If we can find some rules to simulate the distortion in these complex cases, the

**Table 2. Comparison of recognition performance among different approaches on silhouette sequence version 2.1 (Legends: baseline - USF baseline algorithm [9]; real - proposed real gait feature classifier; synthetic - proposed synthetic gait feature classifier; fusion - proposed gait feature fusion.)**

| | Rank1 Performance | | | | Rank5 Performance | | | |
|---|---|---|---|---|---|---|---|---|
| | baseline | real | synthetic | fusion | baseline | real | synthetic | fusion |
| A | 73% | 87% | 83% | 91% | 88% | 92% | 92% | 94% |
| B | 78% | 85% | 94% | 94% | 93% | 93% | 96% | 96% |
| C | 48% | 76% | 61% | 81% | 78% | 89% | 91% | 93% |
| D | 32% | 31% | 50% | 51% | 66% | 58% | 68% | 85% |
| E | 22% | 30% | 48% | 57% | 55% | 60% | 69% | 79% |
| F | 17% | 18% | 22% | 25% | 42% | 36% | 50% | 52% |
| G | 17% | 21% | 33% | 29% | 38% | 43% | 55% | 57% |
| H | 61% | 63% | 48% | 62% | 85% | 90% | 80% | 89% |
| I | 57% | 59% | 52% | 60% | 78% | 81% | 78% | 86% |
| J | 36% | 54% | 34% | 57% | 62% | 79% | 69% | 77% |
| K | 3% | 3% | 18% | 9% | 12% | 12% | 39% | 24% |
| L | 3% | 6% | 12% | 12% | 15% | 12% | 30% | 21% |

recognition performance could be further improved.

## 5 Conclusions

In this paper, we propose a statistical gait feature fusion approach for human recognition by gait. First, each silhouette sequence is divided into cycles. Gait energy images are then computed from each cycle as real gait templates that are insensitive to incidental silhouette errors. We also generate synthetic gait templates by distorting real gait templates. Real and synthetic gait features are extracted by component and discriminant analysis from real and synthetic gait templates, respectively. The fusion rule on real and synthetic gait features is developed for human recognition. Experimental results show that recognition performance achieved by the proposed feature fusion approach is better than that achieved by individual real or synthetic feature classification approaches, and significantly better than that achieved by the baseline frame matching approach.

## Acknowledgments

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